1. Internet of Things (IoT)

IoT is a technology and a concept used to connect every object to the internet. The objects include light, fan, door, human, animals, etc., for various purposes. The world is moving towards the era of smartness and remote monitoring systems. IoT includes multiple domains like the industry domain, agriculture domain, etc. The connected internet objects will be capable of sending and receiving the data known as smart objects. For IoT devices, it is essential to have sensors and actuators. Sensors are required units for data collection to analysis and provide the final results. The healthcare system takes advantage of these IoT devices and doctors connected to the patients proactively to monitor the health at a remote place [18]. The patients are given a very flexible way to know their health information via IoT devices and connect with their respective doctors. As summary, the IoT is defined as "*The Internet of Things (IoT) is a system of interrelated computing devices, mechanical and digital machines, objects, animals or people that are provided with unique identifiers and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction*" [10]. The top advantages of IoT are

- **Connectivity**: It is possible to have a single device to control multiple objects and stop manual operations of the various tasks.
- **Efficiency**: As most of the objects are connected, the amount of time to perform the task is reduced.
- **Convenience**: IoT devices makes us convenient to control the object from the remote place
- **Wellness**: There are few IoT devices that monitor the health and gives suggestions/warnings. For example, smart watches.
- **Conservation**: IoT devices prevent the wastage of resources as it is an automated process.
- **Personalization**: IoT devices are also like personal assistance that learns our likes and dislikes and act accordingly.

Due to the above advantages, many applications use the concept of IoT. The various health care applications proved that IoT could be used on animal health monitoring systems.

2. Internet of Animal Health Things (IoAHT)

Animals are an essential part of our society, so monitoring animal health is crucial and necessary to the respective industry. The sensors are used to monitor animal health and connect these sensors to the internet. Using IoT on animals for health monitoring is known as Internet of Animal Health Things (IoAHT) [8]. This IoAHT helps animal science a lot and provides advantages to pet lovers. There are two ways to deploy sensors on the animals

1. Active sensors: sensors are deployed on the animal body for a long time to monitor the behaviour and health.
2. Passive sensors: The sensors are kept on the animal for a short period of time to monitor the animals behaviour and health,

As per the study, deploy suitable sensors on animals for a long time or short time to monitor animal health and behaviour.

3. Clinical mastitis of cows

One of the major applications of IoT is in dairy industries, which comes under veterinary science. India is the largest milk-producing country globally, accounting for approximately 22 percent of the total milk produced globally [29]. The cow forms are the most crucial resources for any dairy industry and are one of the milk's primary sources. To obtain a significant production in the quality milk, the dairy industries need to ensure cows' well-being, one of their top priorities. Similar to humans, cows, too, experience a wide range of diseases.

A cow needs to be healthy to produce quality milk and every dairy industry needs to ensure the well-being of this domestic animal, which forms one of its topmost priorities. Like humans, animals are also prone to a variety of diseases. One such condition is clinical mastitis, the infection of the mammary glands caused by bacteria entering the udder through the teat ends [28]. Mastitis occurs at the time of lactation, irrespective of the stages and months. But the cows are more susceptible to the disease in the first month of lactation. Initially, mastitis enters a single teat of the udder and then gradually spreads to the other teats. The condition is highly contagious. Utmost care needs to be taken to ensure the protection of cows.

The milking process is done manually or using automatic milking machines depending on the available cows in usual practice. However, in dairy industries, where there will be a massive population of cows, automatic milking machines are employed to extract milk. In such scenarios, it becomes highly challenging to identify the cows infected with clinical mastitis. The clinical mastitis is detected based on the visible abnormalities of the milk, the udder or both. The symptoms of clinical mastitis shown in table 1. The healthy and normal udder is shown in figure 1 for differentiation.

Table 1: Clinical mastitis symptoms [36]

Abnormality in	Parameters	Effects	Results in
Milk	Texture of milk	Flakes	Bad quality milk
		Clots	
		Watery Appearance	
Udder	Hardness	Pus formation in the udder	• Reduction in milk quantity • Bad Quality milk
	Redness	pH value variation	
	Acute pain and sensitivity to touch	Fever in cows	

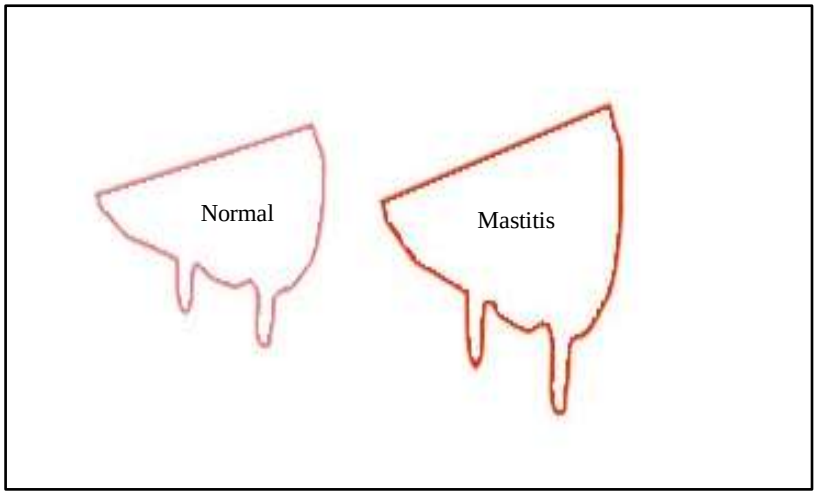

Figure 1: Udder variation in cows

Mastitis can be mild, moderate, or severe, depending on the identified mastitis stage. Identifying mild clinical mastitis is very challenging, whereas, for moderate and severe levels, the cost incurred in identifying and treating mastitis is enormous. Broadly, clinical

mastitis is identified in either a moderate or severe stage, which affects the dairy industries adversely. The proposed work's main objective is to provide an IoT and deep learning-based solution to identifying the clinical mastitis at the early stage, i.e., mild. In this work, animals are being connected to the internet via sensors, IoT, which is referred to as the Internet of Animal Health Things (IoAHT).

4. Literature Survey

The proposed work divides the literature survey into the following parts:

a) Review of sensors used on animals.
b) Review on IoT in veterinary science.
c) Survey on clinical mastitis detection in cows.
d) Review on communication protocols.

4.1 Review of sensors used on animals

Authors concentrated on medical-related sensors and connected the same to servers using gateways [4]. These sensors are deployed in a patient body to get an ECG (Electro Cardio Graphic), body temperature and blood oxygen saturation. ECG is a vital parameter in health issues and suitable sensors are used to monitor this ECG. These sensors are used practically on the animals and recorded no harm to the body.

Light sensors are used to track the animals and this data is transmitted to the Android supporting mobile [6]. The light sensor is replaced with motion sensors to decrease the system complexity. Using Google map service in an Android OS location of the animal can be detected. Using environmental sensor data about the humidity and the temperature are collected. This information about the animal is transmitted to the mobile via SMS. An animal's illness is from the inner stress and the environment, so it is necessary to monitor animals concerning the ecological condition.

The sensors match a reindeer calf with the respective mother [25]. Calves are facilitated with an RFID tag to get the identity of each calf. The RFID tag helped to monitor and track calves in a small cage. Initially, RFID is facilitated randomly to every reindeer cow and calf also kept for monitoring. The permanent RFID is assigned to the cow once after the calf finds its mother. When there are many calves, it is challenging to match with their respective

mother, so this paper proposed a technology that helps a farmer to match calves with its mother and give the same RFID tag for future processes.

Moosense is a wireless sensor network for animal management systems [32]. This system uses temperature sensors and climate control to make the animals free from external constraints. This system monitors Sahiwal's health in breed cows based on feed, fluid, and activity monitoring. Further analysis was done at the server by receiving the data from a client end.

Using Unmanned Aerial Vehicle (UAV) and static wireless sensors, animals are monitored [20]. Divide the region into a predefined grid and deploy sensors called a cluster. Every node in the cluster is known as a cluster associate. The cluster associate gathers and transfers the data to the cluster head. UAV is a wireless destination that collects the information from the cluster head by flying towards every cluster. The results are proved in the simulation environment on the real-world movement dataset of zebras.

Parkinsonian patients suffering from Freezing of Gait (FoG) are monitored and managed remotely [22]. In this system, the data related to the FoG are collected using a Smartphone, which acts as a monitoring device. Initially, the local database stores these data using the respective app and forwards them to the central database through the internet. To make data accessing easier, the web app provides the user interface for queries. The result was proved on six Parkinsonian patients, along with FoG detection accuracy and effectiveness. Lots of research is taking place to detect Parkinsonian disease concerning various parameters.

Fabien Hoflinger *et. al.* introduced dual innovative motion capture sensors to screen motoric dysfunction in laboratory animals [12]. To detect multiple sclerosis, active and passive sensors were used. Active sensors store the data in an SD card and use battery power. A passive sensor uses power from an electromagnetic field. The active sensor is put inside the bag and placed on the animal's back. The passive sensor is placed in a small pen and allowed to collect the data. Here the experimental autoimmune encephalomyelitis (EAE) animal model was applied. The healthy animal showed expected behaviour and jumped, but the remaining animals escaped jumps and turns. Active and passive sensors are the name given to sensors based on their usage. Active sensors are dynamic, whereas passive sensors are static in their actions on the animals.

J. Lu et al. developed implantable sensors to collect biotic data on an animal [19]. These data helps detect the diseases in the animal health care system and monitor the external parameter.

The implantable blood pressure sensors monitor animals in the laboratory and it is an easy task [41]. The pressure sensors monitor the animal's physiological conditions and give the information remotely. These sensors effectively reduce moisture dispersion.

Hai Wang *et.al.* proposed "A Wireless Sensor Network for Feedlot Animal Health Monitoring System" to detect illness at the early stages [15]. In this system animal's ear is tagged with Electronic radio frequency Identification (EID). This EID repeatedly records the animal behaviour. Two types of data parameters are chosen food bunk and water trough. Based on the intake of food and water, animal conditions of health are monitored. The healthy animal will have food and water in a balanced manner and improper food and water taken by the unhealthy animal.

A Krvavica *et.al.,* proposed "Comparison of Electrocardiographic Monitoring and Standard ECG in Dogs" [2]. ECG data from a dog is collected using suitable sensors on the body. Two types of ECG devices are used, standard ECG and a wireless electrode ECG. For every two minutes, the ECG of the dog was recorded from a standard ECG device and compared with fifteen-minute ECG data collected from the wireless electrode. This paper proved that both ECG methods give a similar result.

Bats are identified and restricted in their expected environment using sensor nodes [23]. In the animal monitoring system, animal's movement observation and interactions are crucial. Bats are readily available, and monitoring them in their natural habitat for localizing and monitoring gives animals' excellent research. The two places Gamboa and Panama, are chosen to do the field test.

Kriti Bhargava *et. al.,* designed a "Fog-enabled WSN system in Precision Dairy" to analyse animal behaviour [21]. The animals wear sensors to collect behaviour data. This paper proposes a system to analyse the behaviours of dairy cows. This method uses a collar device to collect the data and explores the same locally also restricts cows' movement inside the given boundary, lastly sending these local stored data to the cloud storage using WiFi. The data in the cloud could be analysed and detects the improper behaviour of cows in dairy.

The summary of the review of sensors on the animal is shown in table 2. Sensors are like a basic IoT unit, which collects the data and sends it for analysis. Usually, the sensor will not harm if used appropriately. The above surveys proved that sensors could be used on humans as well as on the animal body. The sensors are utilized on animals for various reasons like to detect disease, but utmost care to be taken while using sensors on the animal body.

4.2 Review on IoT in veterinary science

Anushka Patii proposed a "Smart Health Monitoring System" [3]. The temperature sensors track the animal's body temperature. The humidity sensor identifies the effect of environmental conditions on the animal body. Heart rate sensors give data about the unbalance in the heart rate of an animal. Digestion is also one of the significant factors of animal illness. The rumination sensor monitors the digestion process in the animals. Based on these four sensors, animal health is monitored and treated regularly.

"Real-Time Signal Quality-Aware ECG Telemetry System for IoT-Based Health Care Monitoring" was proposed by Udit Satija *et. al.*, [37]. Using IoT-enabled signal quality-aware ECG Telemetry system, cardiac health issues are monitored. The proposed system proved the ECG signal dataset taken from MIT-BIH arrhythmia, Physionet Challenge databases and recorded ECG signals under different physical activities. This system has taken advantage of a cloud storage service to store acquired ECG signal data.

To screen and control aquaculture, Wen-Tsai Sung *et. al.*, proposed a "Multi Sensors Real-time Data Fusion Optimization for IoT Systems" [40]. Smart health monitoring systems are used to monitor fish using three kinds of sensors. The temperature sensor provides the temperature, the oxygen sensor to detect the oxygen level, and the pH sensor to find the water's pH level. The data from the sensors stored in the cloud and the same is analysed. An efficient user interface is provided to view the analysed results.

Chao-Hsi Huang *et. al.*, proposed an "IoT-Based Physiological and Environmental Monitoring System in Animal Shelter" [7]. The efficient algorithm is developed based on physiological and environmental criteria to increase the stray animal's adaption rate in an animal shelter. The results are given in three modes, normal mode to indicate the safe situation, error mode to provide error situation and warning mode to display a dangerous situation.

Table 2: Summary of sensors on animals

Sl. No.	Title	Sensor	Purpose
1	Embedded Discrete Passives Technology for Bandage-Type Medical Sensors of E-healthcare System [4] *IEEE, 2011*	Medical sensors	To acquire signals such as ECG (Electro Cardio Graphic), body temperature and blood oxygen saturation.
2	Mobile Animal Tracking Systems Using Light Sensor for Efficient Power and Cost Saving Motion Detection [6] *IEEE,2012*	Light sensor, Environmental sensor	To track the animals.
3	Matching Mother and Calf Reindeer Using Wireless Sensor Networks [25] *IEEE,2013*	RFID	To match reindeer calf and mother.
4	Development of a Wireless Sensor Network for Animal Management: Experiences with Moosense [32] *IEEE,2014*	Temperature sensors	To monitor the health of Sahiwal breed cows.
5	Animal Monitoring with Unmanned Aerial Vehicle-Aided Wireless Sensor Networks[20] *IEEE,2015*	Unmanned Aerial Vehicle (UAV) and static wireless sensors	Animal monitoring.
6	An Architecture to Manage Motor Disorders in Parkinson's Disease [22] *IEEE, 2015*	The smartphone acts as a sensor	Parkinsonian patients suffering from Freezing of Gait (FoG) are monitored.
7	Motion capture sensor to monitor movement patterns in animal models of disease [12] *IEEE,2015*	Active and passive sensors	to monitor motoric dysfunction in a laboratory animal's
8	Miniaturization and Packaging of Implantable wireless sensor nodes for Animals Monitoring [19] *IEEE,2016*	Implantable sensors	For collecting biological information of an animal.
9	Robust Implantable Blood Pressure Sensor Packaging for Long-Term Laboratory Animals Monitoring [41] *IEEE,2016*	Implantable blood pressure sensors	Animal monitoring system.
10	A Wireless Sensor Network for Feedlot Animal Health Monitoring [15] *IEEE,2016*	Electronic Radio Frequency Identification (EID)	To monitor feedlot animal health.
11	Compression of Wireless Electrocardiographic Monitoring and Standard ECG in dogs [1] *IEEE,2016*	Wireless electrocardiographic) sensor	To record ECG data.
12	Low-weight Wireless Sensor Node for Animal Encounter Detection and Dual-band Localization [23] *IEEE,2016*	Accelerometer	The orientation of the bat's body is detected to recognize resting phases.
13	Fog-enabled WSN System for Animal Behavior Analysis in Precision Dairy [21] *IEEE,2017*	Active sensor	To analyse the behavior of dairy cow.

Anitha Ilapakurti and Chandrasekar Vuppalapati proposed "Building an IoT Framework for Connected Dairy" [2]. The heat pressure is a parameter, which decreases milk production in cattle. If the cow is glad, then there will be a growth in milk production. The designed electronic monitor system detects a cow's temperature variations and disorder in the dairy

industry to exploit the profit also ducks the death caused by heat pressure. It uses Bluetooth equipment for connectivity. The trained data warehoused in the cloud for upcoming real-time data analysis.

Wi-Fi is the most excellent connectivity resolution for IoT [34]. All animals are organized with Neighbour Awareness Network (NAN) only IoT sensors to track an animal's position in a jungle. The vehicle with a NAN permitted display to get information about the animals.

Muhammad Hunain Memon *et. al.,* proposed an "Internet of Things (IoT) Enabled animal farm" [26]. A smart animal form, along with suitable sensors, will monitor animal behaviour. Food and water are the primary requirements for the animals. These requirements are fulfilled automatically and dynamically without human effort. Biogas provided by the animal may provide fire and using suitable sensors, a fire protects the farms. The temperature is under control using a heater and fan. IP camera monitors the animals remotely on a computer or smartphone display.

Sangeetha Rajesh developed a "Ubiquitous Energy Efficient Aquaculture Management System" [33]. The robotic system remotely monitors fish activities and saves fish. The proposed method uses suitable sensors like temperature sensors, oxygen sensors, nitrogen sensors, pH sensors, and reliable sensors to monitor aqua creatures. The statistics are collected from sensors are transferred to the internet and analysed to give the appropriate result. The respective changes to the monitored parameter are applied dynamically without human intervention.

Michael Schadhauser *et.al.,* proposed the idea "Adaptive Low Power Wide Area (LPWA) Bat Communication Network" [24]. A wireless sensor network tracks the bats using many light weight Ultra Low Power (ULP) sensor nodes. These sensors are fixed to the rear of the animals. This method aims to provide an idea, to use ULP sensors on tiny and light weight animals for tracking.

Namkyung Lee *et. al.,* proposed a "Things-Aware Smart Pet-Caring System with the Internet of Things on Web of Object Architecture" [27]. This method uses the Web of Objects Architecture (WoA) to love pets, which provides web services through sensor gateways. This gateway is responsible for the device connections and collecting the information. This approach uses an existing protocol named International Protocol

TeleVision (IPTV). A sensor collects the pet-related data and transmits it to the pet owner resides in a distant place. The enabled video-on-demand makes pet masters watch the pet condition lively. The high-quality camera gives the best quality video of a pet. There is no delay in video and audio-video consistency, which is well maintained.
The summary of the review on IoT in veterinary science is shown in table 3.

4.3 Survey on clinical mastitis detection in cows

IoT is not introduced to detect clinical mastitis till date. The detection of mastitis in veterinary science is based on the Somatic Cell Count (SCC) of milk [16]. E. Wang and S. Sama- rasinghe worked on mastitis detection using the parameter listed in table 4 [11]. Clinical mastitis is detected using the parameters like Somatic cell count of milk, colour sensors, and milk's electrical conductivity. Table 5 summarizes the parameter and algorithms used to detect mastitis. But these approaches have the following drawbacks,

- The cows are not connected to the internet for live analysis of the data.
- The parameters mentioned above are not sufficient to detect mastitis.
- The process is time-consuming.
- Continuous monitoring is a laborious job.
- Mastitis is detected using the electrochemical properties of milk and advanced technologies are not applied to speed up the process.
- These are not cost-effective.

4.4 Reviews on communication protocols

The review of two sequential decision-making models, namely Markov Decision Processes (MDPs) and Partially Observable MDPs (POMDPs) in health care using the Internet of Things, are done efficiently [9]. The central part of MDPs is rewards or costs and it does not use historical data to produce the result. Process state and control actions are two inputs to the MDPs. In POMDP, conclusions are taken based on the historical observation and control functions, but data are hidden.

Table 3: Summary of IoT in veterinary science

Sl. No.	Title	Outcome	Drawbacks	Research Focus
1	Smart Health Monitoring System for Animals [3]. *IEEE,2015*	Animal health monitoring using temperature, Humidity, Heart rate and Rumination sensors	Parameters are standard in finding different diseases.	Identify the parameter which is unique to find disease.
2	Multi sensors Real-time Data Fusion Optimization for IoT Systems [40] *IEEE,2014*	Temperature, Oxygen and pH sensors monitor the fish.	Monitors and controls only the most primary function.	Analyzing the most suitable environment outside the farmed fish industry.
3	IoT-Based Physiological and Environmental Monitoring System in Animal Shelter [7] *IEEE,2015*	An animal monitoring algorithm to increase the adoption rate of the strays in the animal shelter.	Sending alert message to manager and veterinarians.	Improve the current algorithm so that it can be applied for more stray animals.
4	Building an IoT Framework for Connected Dairy [2] *IEEE,2015*	Detecting the cow's temperature and ill-ness in the in- dairy industry to maximize the profit also avoids the death caused by heat stress.	The nature of cows changes with respect to the environment and it is difficult to generalize the symptoms.	Improve current algorithm to provide more milk.
5	WiFi-Aware as a Connectivity Solution for IoT [34] *IEEE,2016*	Track an animal position and displays the same at a remote location	All Animals are deployed with a sensor on their body and the vehicle is installed with a NAN enabled display.	Design a plug and play device.
6	Internet of Things (IoT) Enabled Animal Farms [26] *IEEE,2016*	The feed and water are smartly provided to the animals using sensors.	Every individual animal has its capacity to consume food so setting a threshold is challenging.	Analyze individual animal food data.
7	Ubiquitous Energy Efficient Aquaculture Management System [33] *IEEE,2016*	It is an automated system to save fish.	The requirement of water environment varies based on the types of fishes.	Creating the Automatic Feeder and Analyzing water density requirement.
8	Things-Aware Smart Pet-Caring System with the Internet of Things on Web of Object Architecture [27] *IEEE,2016*	Sensors are used to collect the pet data and send it to the pet master remotely.	How frequently the owner checks the data.	How far it is feasible in practice.

Table 4: Clinical mastitis parameter

Sl. No.	Parameter
1	Milk pH
2	Electrical Conductivity (EC) in mS/cm
3	Udder Temperature(˚C)
4	Milk Temperature (˚C)
5	Skin Temperature (˚C)
6	Milk Somatic Cell Count (SCC) in 1,00,000 cells/ml
7	Milk Yield (kg)
8	Dielectric Constant

Every scholar has been used wireless sensors to examine and trail the wild animals. Low Energy Adaptive Cluster Hierarchy (LEACH) is one of the routing protocols of wireless sensor networks. The protocol is used to provide efficient communication between sensor nodes [30] [39]. LEACH uses a clustering conception for communication. The cluster head is responsible for sending the sensed data to Base Station (BS) for results. Every cluster members convey the information to the cluster head. Base Station's responsibility is to find the cluster head near the cluster members for further communications and transmission. LEACH protocol chooses a cluster head on an alternation basis to have maximum energy to provide better performance.

Distributive Energy Efficient adaptive clustering (DEEAC) is also a routing protocol for wireless sensors. It has two phases set up and a steady phase. DEEAC is also a clustering-based protocol with cluster leader, cluster associate, and remote BS. DEEAC uses delivery rate as a metric to choose the cluster leader. DEEAC targets the region of high generated data rate called the hot area. The node in this area will become a cluster leader to transmit the BS data and with less energy. In DEEAC, the node near the hot region has a high probability of becoming a cluster leader and energy consumption in the wireless sensor networks is optimized. Since tigers live together, for monitoring, sensors are deployed on them. DEEAC is a suitable proto- col for communication [30][38].

When all objects are connected to a network for communication, security is a big issue. MQTT (Message Queue Telemetry Transport) and CoAP (Constraint Application Protocol) are two efficient communication protocols. There are still more IoT communication protocols based on various applications.

Table 5: Summary of sensors and algorithm used to detect clinical mastitis

Sl. No.	Definition cases (n)	Sensors	Algorithm	Sensitivity %	Specificity %
1	Clinical mastitis based on clinical signs (52 cases) [16]. *Journal of dairy science, 2010*	EC, milk yield, milk temperature.	Time-series with Kalman filter	90	98.2
2	Clinical mastitis based on clinical signs (48 cases) [16]. *Journal of dairy science, 2010*	EC, milk yield, Milk temperature.	Time-series with Kalman filter.	100	95.1
3	Clinical mastitis based on clinical signs (48 cases) [16]. *Journal of dairy science*	EC, milk yield, milk temperature.	Fuzzy Logic.	100	99.8
4	Clinical mastitis based on visual observation (95 cases) [16]. *Journal of dairy science, 2010*	EC, milk yield, milk temperature.	Time-series with Kalman filter.	674	97.9
5	Clinical mastitis based on treatment by veterinarian after observing clinical signs by staff members (275) [16]. *Journal of dairy science, 2010*	EC.	Discriminant function analysis.	47.9	91.9
6	Clinical mastitis based on treatment (651days of mastitis for training; 348 days of mastitis for testing) [16]. *Journal of dairy science, 2010*	EC, milk yield, milk flow.	Fuzzy logic.	92.9	93.9
7	Treated cases of Clinical Mastitis (18 cow milking) [16]. *Journal of dairy science, 2010*	EC, SCC.	Fuzzy logic.	80	99.2
8	Clinical mastitis as clots on filter (23 in test set) EC [31]. *New Zealand veterinary journal, 2009*	EC.	Threshold.	83	99.8
9	Clinical mastitis based on visual observation of abnormal milk (19 quarter milk images) [14]. *Journal of dairy science, 2010*	EC, SCC.	Threshold.	47.4	99.0
10	Based on visual observation by farmers (97 quarter milking) [13]. *Elsevier, 2010*	EC, color, milk yield.	Decision-tree induction.	32.0	98.7
11	Based on visual observation by farmers (243 for training; 105 for testing) [5]. *Journal of dairy science, 2010*	EC, color milk yield.	Decision-tree induction.	40.0	99.0
12	Clinical mastitis based on SCC (895 quarter milking) [42]. *Journal of dairy research, 2010*	EC, milk yield.	Artificial Neural Network.	86.9	91.4

4.5 Challenges

The following are the few challenges to be faced with detecting clinical mastitis in cows.

- The cow health monitoring system must be accurate and dynamic.
- The data set for analysis is not readily available for prediction. The existing dataset is on milk, which is insufficient to detect clinical mastitis as milk properties change based on many factors.
- Every individual must be trained to use the system for further prediction.
- All veterinary doctors do not know engineering technology/computer science and vice versa.
- Working on cows requires lots of groundwork and behaviour analysis.
- Tough to decide on sensors with low cost and desired results.
- Taking images of the cow is one of the biggest challenges with proper light and pose
- Lots of trial and error has to do before using sensors.
- Fixing sensors to the cow udder was the most significant challenge. Lots of ideas were tried but failed in the beginning.
    - As animals will not bear the irritations on their bodies, placing sensors or making animals present near the sensor is a tedious job.

4.6 Opportunities

The following are the few opportunities for research

- Develop a system to find the health issues of a cow which affects the economy and endangered species.
- Train the farmer to use the workshop and develop a user-friendly interface or app.
- Collect the data from primary observation and publish it for further analysis from various researchers.
- The collaboration of veterinary doctors and engineers/science graduates gives a reasonable contribution to cow health and clinical mastitis.

- Keep a sensor on the body of a cow or any animals for a short period of time.

5. Problem Statement

India has approximately 150 million cows, with each of them providing an average of less than 200 litres of milk per year [17]. The estimation is further impacted by various external factors, with one being disease. If appropriate treatment is given at the right time, the cows can provide up to 11,000 litres of milk. The milk being one of the most essential commodities is getting expensive by every passing day. With improved production, we could become the world's leading exporter of milk and its products. Like human beings, the animals too are susceptible to various kinds of diseases. One of the most common diseases that is commonly found in the cow is clinical mastitis. The clinical mastitis is a dangerous disease, which is highly contagious among the cows. If attention and medication is not provided at the right time, it may lead to the death of the cow.

In most of the cases, the farmers are not able to identify the mastitis, or they may ignore it due to the lack of awareness regarding the disease. In the present scenario, there are technologies available, which help them in detecting the disease, whose results are closer to the reality. It is possible to detect the clinical mastitis in the clinical stage. However, treatment has to be provided within 24 hours, failing which the cow will die, thereby affecting the farmers and the dairy industries adversely.

Few methods are developed to identify clinical mastitis based on the milk properties but are not sufficient parameters to detect clinical mastitis. Udder health also matters to occur clinical mastitis, so udder parameters also play a significant role in finding clinical mastitis in cows. ***Therefore, the research aims to solve this problem by developing a system to detect clinical mastitis in cows using IoAHT.***

6. Objectives

The proposed research objectives are focused on developing a prototype to detect clinical mastitis in cows. The following goals are determined:

1. Identify the challenges and opportunities in detecting clinical mastitis in cows
2. Designing a system to collect data from cows :

As the data is not available for the research, the second goal is to collect primary data. This objective is accomplished using the hardware system.

3. Developing an algorithm to predict clinical mastitis in cows:
   An efficient algorithm to be applied to predict clinical mastitis in cows.

7. Methodology to detect clinical mastitis in cows

The research methodology is defined as a systematic process of collecting, organizing, synthesizing, analysis and interpreting data to enhance the necessary knowledge about the phenomenon or object under investigation. The proposed work aims to collect data from the available cows in the local region. These gathered data are trained and kept in the cloud for further analysis. A suitable algorithm is applied to the dynamic test data to get the result.

Figure 2 shows the basic model to detect clinical mastitis in cows. The sensors collect the udder data and temperature data for analysis. These data reside on the cloud or any means of storage centrally for further processing. Various local regions visited to experiment with the sensors and to collect the samples. The model experiments with the train and test data accurately to detect the clinical mastitis in cows. The proposed method helps the veterinary science and large-scale dairy industries to improve economically and detect clinical mastitis at the early stage. The data must be collected from the field and divided into a training set and test set for further analysis using a suitable algorithm.

A detailed view of the process is shown in figure 3. The process is divided into two parts are,

1. User end process
2. Cloud end process

At the user end process, data gathering takes place using a sack, switch and a camera. The sack collects the sensor data from the udder and the switch in hardware gives manual input about the hardness of an udder. The sensor data includes four flex sensor readings and a temperature sensor reading, which are essential for clinical mastitis analysis. The camera collects the milk images of cows for further analysis. Data acquisition is the first stage and done by using a hardware sack and the camera.

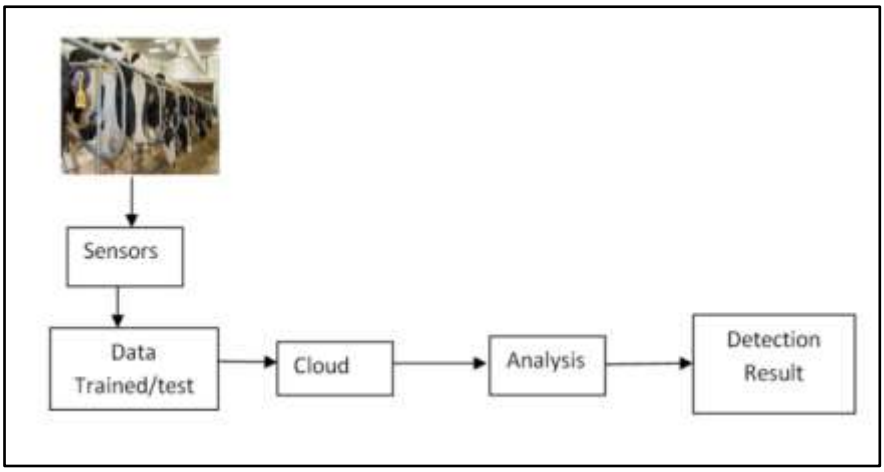

Figure 2: Conceptual model to detect clinical mastitis

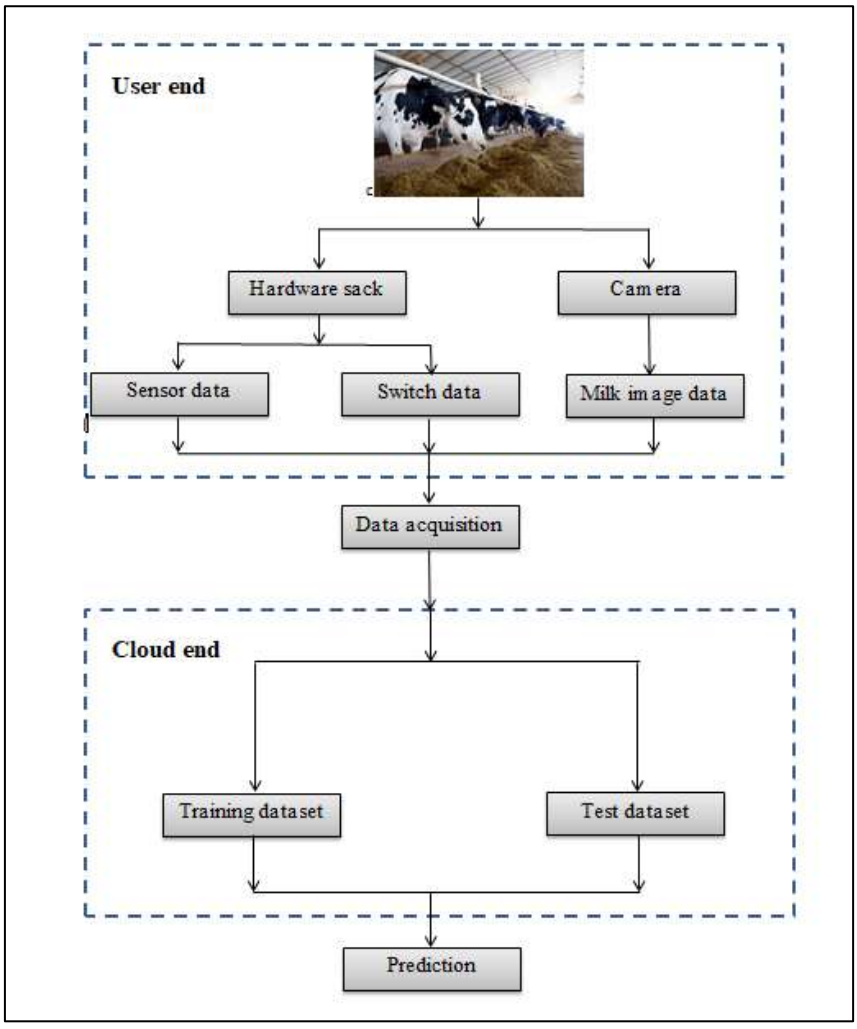

Figure 3: Detailed system architecture to detect clinical mastitis

The gathered data is divided as a trained set and test set so that a suitable algorithm is applied to detect clinical mastitis in cows at the cloud end. The purpose of the cloud is for storage and data analysis carried out here. The plan is to choose basic machine learning algorithms and apply deep learning concepts later on stage for analysis.

Based on the respective advantages over other existing algorithms, the following are chosen to analyse the result of clinical mastitis detection.

1. K-Nearest Neighbour Algorithm (KNN)
2. Support Vector Machine (SVM)
3. Random Forest Algorithm (RF)

The above mentioned are machine learning algorithms that mention the features for analysis beforehand. The Convolution Neural Network (CNN) is applied to milk images to analyse milk for normal and abnormal. The deep learning concept is used on the dataset to prepare the model for analysis. The neural network automatically takes the features to detect clinical mastitis in cows.

8. Hardware system to detect clinical mastitis

For collecting the data, first, a sack containing all the required sensors is designed. The sack acts like a cow bra, covering the udder and the teats shown in figure 4. The sack consists of four flex sensors, a temperature sensor and a switch to generate the required data for mastitis detection in cows. The sample of the data collection process is shown in Figure 5. The sensors touch the cow's udder and body to fetch the values, but there is no harm to the cow from these sensors. The water content after washing the udder to be dried off before using the sack and lactation process.

The sack contains the following to collect the data for the chosen parameters of clinical mastitis detection.

a) Flex sensors

b) Temperature sensors

c) Analog to digital converter

d) Raspberry pi

e) Switch

Figure 4: A cow bra covering the udder

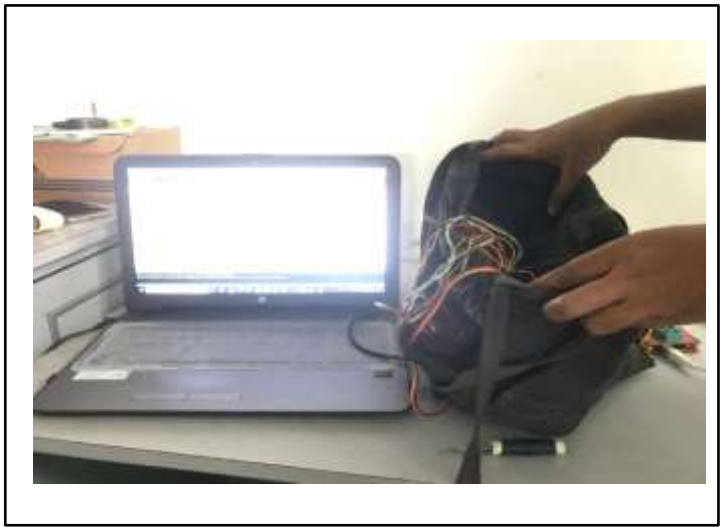

Figure 5: A sack to detect clinical mastitis

8.1 Flex sensor

As per the literature review, it is found that the primary symptom of a mastitis cow is the variation in the udder size due to swelling. The udder has four teats and initially, the mastitis infection occurs in any one of the teat quarters. The teat quarter is sketched in figure 6. The infected teat quarter will be lead to the swelling in the udder, which is detected using a flex

sensor. It is possible to monitor the swelling of the udder using four flex sensors with respect to the quarters of an udder.

The flex sensor is shown in Figure 7. The proposed hardware uses a 4.5-inch flea sensor, which gives the value based on its bent. The flex sensor has two terminals. Due to the absence of a diode, the flex sensor does not contain positive and negative ends.

The flex sensor has two pins as follows

a) P1: This pin connected to the positive power source

b) P2: The pin P2 connected to the ground

The flex sensor features are,

- The flex sensor operating voltage is 0.5V.
- It can operate in low voltage.
- The flex sensor power rating is 0.5watt (continuous) and 1 watt(peak).
- Flex sensor works under the temperature of -45^0 C to + 80^0 C.
- 25KΩ resistance is an advantage of the flex sensor.
- Resistance range while bending is 45K to 125K Ohms.

The flex sensor is suitable for measuring any object's bent or angle change due to the pressure or any other modifications. The value ranges from 0 to 255. The flex sensor is the variable sensor when you bent, its resistance angle increases. Therefore flex sensor is used to intelligence the change in linearity. Figure 8 shows the resistance of sensor value variations. When the flex sensor is flat, it has nominal resistance. The 45^0 bent flex sensor increases the resistance twice as before. The 90^0 bent flex sensor increases the resistance four times than the nominal resistance.

The circuit of the flex sensor is shown in figure 9. The V_0 is extracted using equation (i).

$$V_0 = VCC\left(\frac{R_x}{R_1+R_x}\right) \text{ ---------- (i)}$$

Where,

V_0 is the output voltage,

VCC is a power supply,

The R_1 is resistance with a constant and R_x is a flex resistance

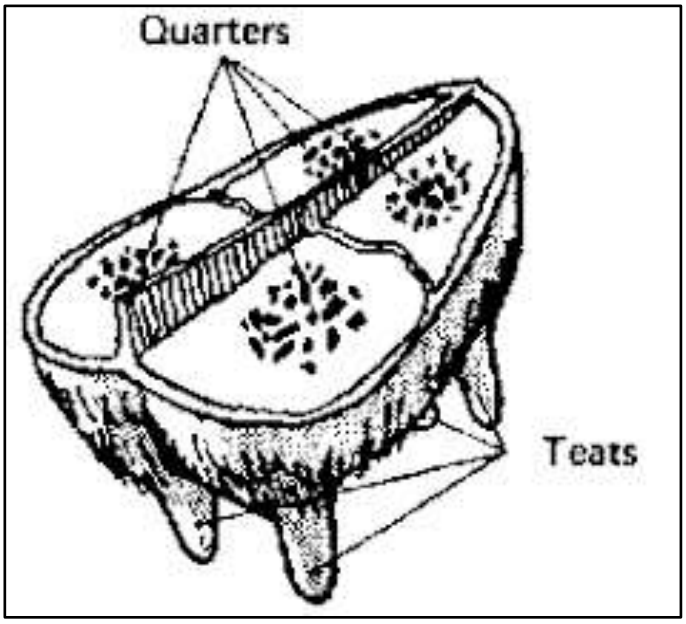

Figure 6: The teat and quarters of an udder

Figure 7: The details of the flex sensor

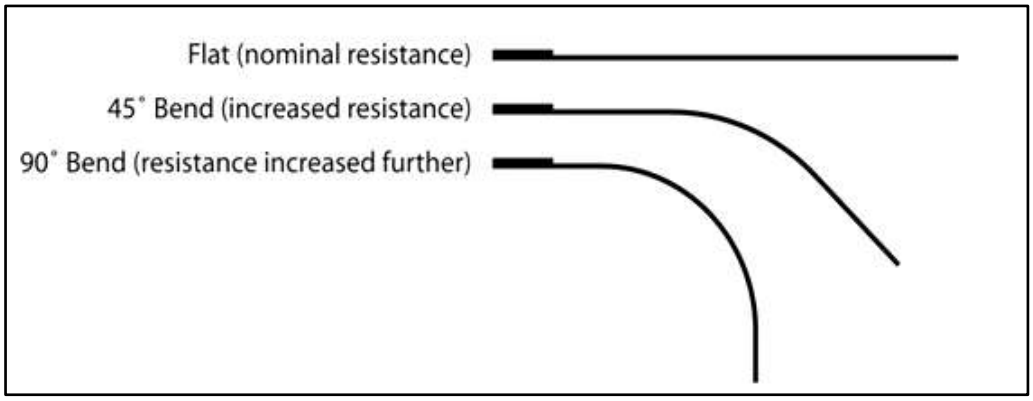

Figure 8: flex sensor resistance value

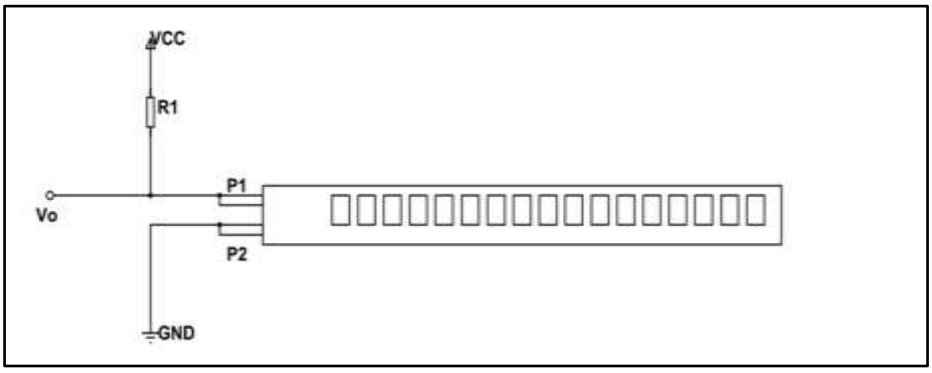

Figure 9: The flex sensor circuit

8.2 Temperature sensor

Udder swelling indicates infection, which leads to an increase in the udder temperature. The udder temperature is noted using a temperature sensor. A sample temperature sensor is shown in Figure 10. The pin information of the temperature sensor is explained in figure 11.

The following are the pin description of the LM35 temperature sensor,

P1: VCC, which takes the voltage of +5v.

P2: It provides the analog output ranges from -1V (-55°C) to +6V (150°C).

P3: This pin is connected to the ground.

Figure 10: Temperature sensor

Figure 11: LM35 temperature sensor pin diagram

The circuit diagram of the temperature sensor is explained in figure 12.

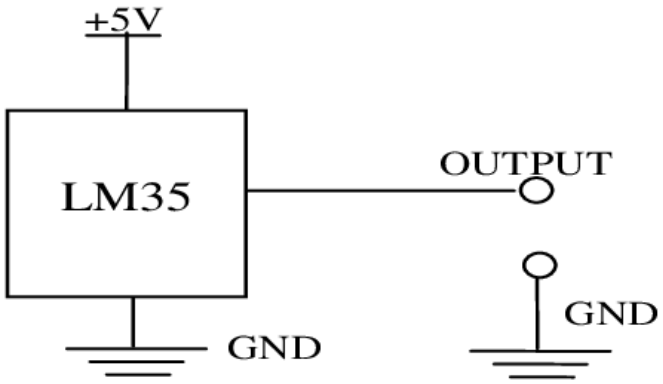

Figure 12: Circuit diagram of the LM35 temperature sensor

The LM35 features are,

- The minimum voltage is 35V and the maximum voltage is -2V
- Measures the temperature ranging from -550C to 1500C
- LM35 is a low-cost temperature sensor
- It is small in size and suitable for remote sensing applications

The V_{out} is calculated using the formula (ii).

$$V_{out} = 10mV/°C \times T \text{ ---------- (ii)}$$

Where,

V_{out} is temperature sensor output voltage

T is the temperature value in °C

$10mV/^0C$ is a linear scale factor

8.3 Analog to digital converter (ADC)

The four flex sensors and a temperature sensor will continuously generate the analog data. An analog to digital converter is required to convert these analog values to digital values. Hence an analog to digital converter is deployed within the sack for the above said purpose. Further analysis is done on the digital data for the detection of mastitis.

The ADC is a data converter integrated with a microprocessor-controlled circuit like Arduino to communicate to the real world. The ADC takes the snapshot of an analog voltage simultaneously and provides the digital value as an output. The pin diagram is shown in figure 13. The proposed work uses the Arduino board for analog to a digital converter where ADC is inbuilt in it. Figure 14 shows the Nano Arduino board used in clinical mastitis detection.

The Nano Arduino has the following pin configuration,

Pin1: It consists of all related to power category like Vin, 3.3V, 5V, GND

Vin: provides the voltage to Arduino when using an exterior power

3.3V: It is the on board voltage regulator

5V: power supply to the other components on the board

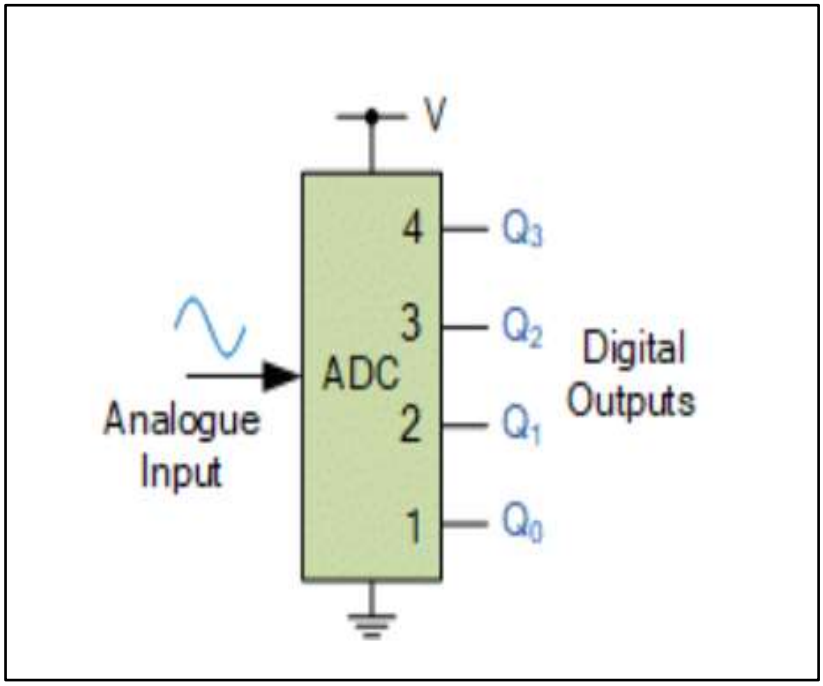

Figure 13: The pin diagram of ADC

Pin2: It reset the Arduino

Pin3: It has eight analog pins to measure the analog voltage indicated as A0-A7

Pin4: This pin is used for input or output indicated as D0-D13

Pin5: Receives and transmits serial data showed as Rx and Tx, respectively

Pin6: This pin used for the interruption and pin number is 2 and 3

Pin7: Provides the pulse width modulation output and pin numbers are 3, 5, 6, 9, 11

Pin8: Serial peripheral interface communication using pins 10, 11, 12 and 13

Pin9: Specifies the inbuilt LED and the pin number is 13

Pin10: This is for two-wire interface communication

Pin11: Provides the reference voltage for input

The Arduino pin diagram is shown in figure 15. Using the Arduino is an easy task. First, required to install the Arduino IDE software, which is open source and connect the Arduino to the laptop or desktop via USB port to run the program.

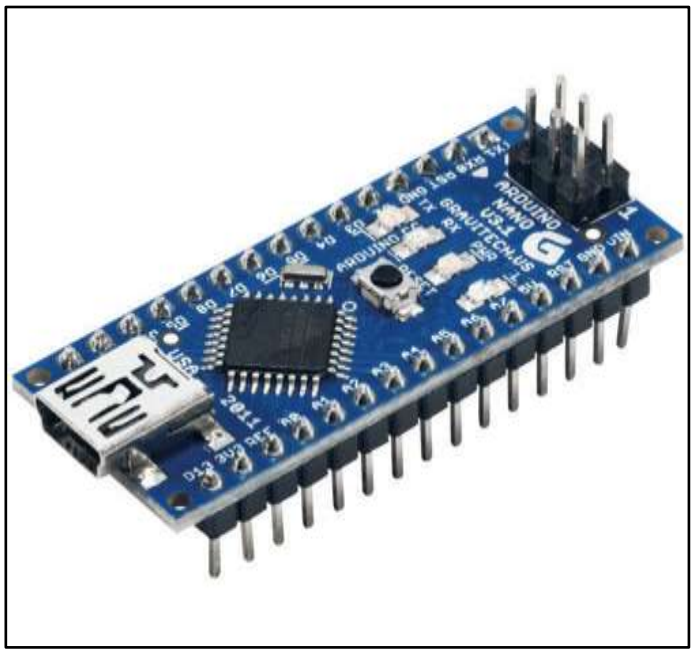

Figure 14: The Arduino

8.4 Raspberry pi

The raspberry pi acts as a sensor node and relays the cloud's digital data. Cloud is an integral part of IoT structure, which is mainly required for storing the data. The pin diagram of the raspberry pi is explained in figure 16.

The raspberry pi has the following pin configuration,

Pin1: For the power source +5V power output,+3.3V power output and ground pin.

Pin2: This includes communication interfaces like receiver and transmitter indicated as Rx and Tx.

Pin3: For peripheral communication using serial peripheral interface.

Pin4: Connects peripherals using a two-wire interface

Pin5: Some pins for input and output

Pin6: The four channels GPIO12, GPIO13, GPIO18 and GPIO19, provides Pulse Width Modulation outputs

Pin7: All the input and output pins act as an interrupts

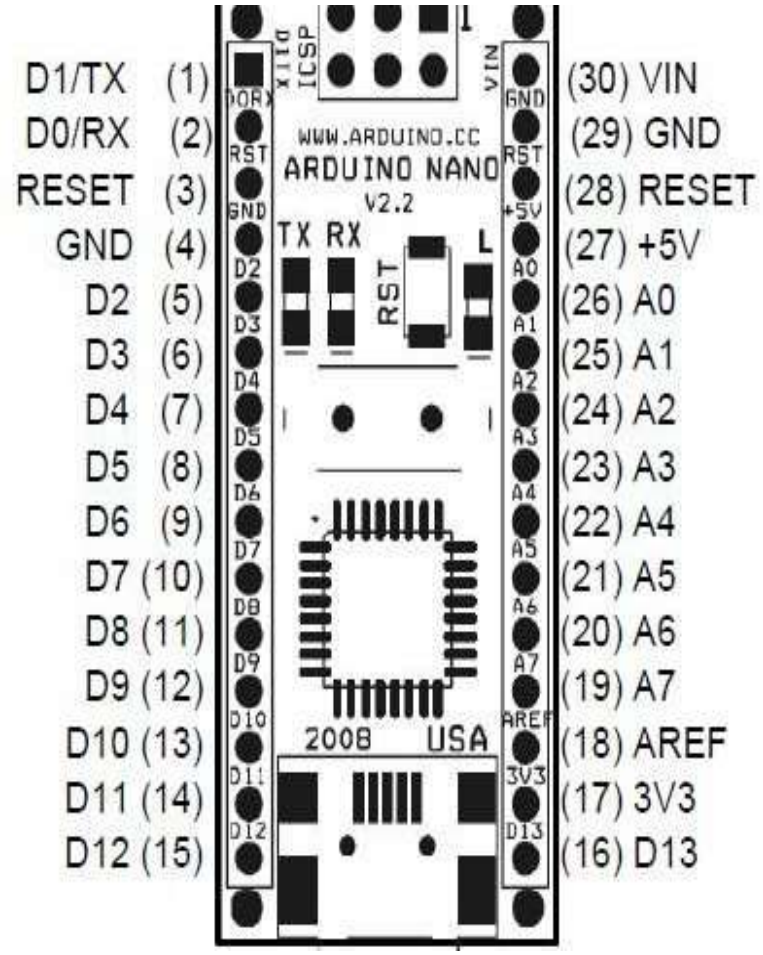

Figure 15: The Arduino pin diagram

Along with the pins, the raspberry pi has the following connectors

- T Ethernet connector
- Four USB sockets of 2.0
- HDMI Arduino output with 3.5mm jack
- HDMI video output

- 15-pin MIPI Camera Serial Interface
- Display connector
- Memory card slot

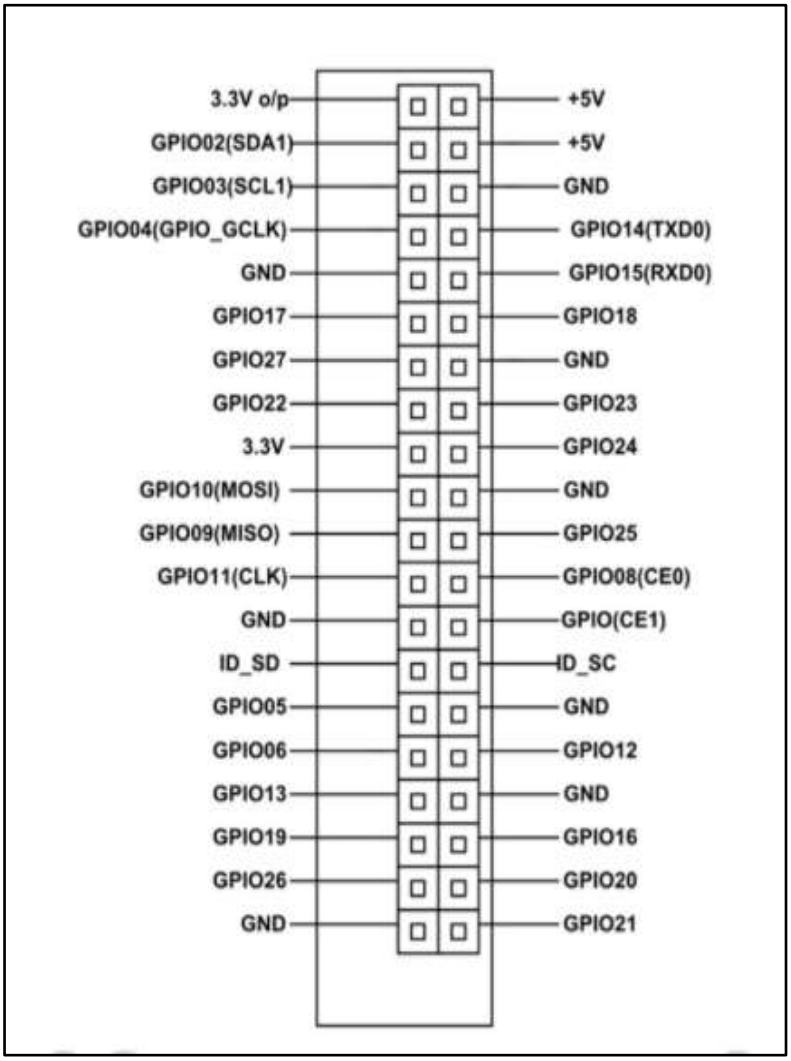

Figure 16: The raspberry pi pin diagram

The properties of raspberry pi make the task easier and faster these properties are,

- Raspberry pi has a 1.2GHz clock speed and 1GB RAM
- Raspberry pi has wireless connectivity via Bluetooth or wireless LAN. It is possible to set up a WIFI hotspot for internet connectivity. Due to these, raspberry pi is best suitable for IoT.

- Raspberry pi have a dedicated port to connect the LCD
- Dedicated camera port in raspberry pi allows the camera to connect

8.5 Switch

The hardness of an udder is also one of the parameters in clinical mastitis detection. It has only two outputs, high (1) and low (0). The sack consists of a normal switch that expects the user's input about an udder's hardness.

In summary, all the sensors and converters are embedded inside the sack. The sack is worn to the cow only twice a day for 5 to 10 minutes before the milking process. Finally, the architecture of the hardware is shown in figure 17.

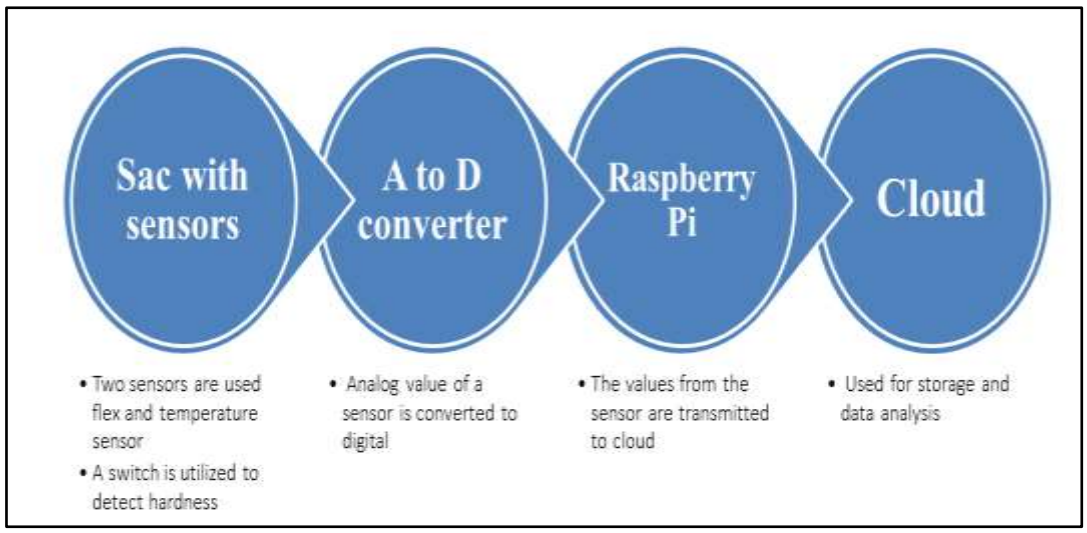
Sac with sensors
A to D converter
Raspberry Pi
Cloud
• Two sensors are used flex and temperature sensor
• A switch is utilized to detect hardness
• Analog value of a sensor is converted to digital
• The values from the sensor are transmitted to cloud
• Used for storage and data analysis

Figure 17: High-level hardware architecture

9. Data for clinical mastitis in cows

As per the literature survey on clinical mastitis, all available datasets are based on the milk properties. Survey also tells that along with the milk properties, the udder data directly proportional to the mastitis in cows. So the proposed work aimed to collect the data from the cow field as a direct observation and publish the same for future analysis.

The data for clinical mastitis is gathered from the various cow fields and becomes primary data without any alteration. The data is collected from the hardware, which is enclosed with

the sensors (flex sensor and temperature sensor), the switch that gives the information about the hardness of an udder and milk images from the camera. The data parameters are listed in table 6.

As a summary, the four flex sensor gives different udder values per quarter, respectively, as an indicator of the swelling of an udder. The temperature sensor is used to detect the temperature variations in the cow. The note here is, due to a pain in the udder, the chances of increasing temperature is more as a sign of fever. Inversely the increase in fever denotes the pain of the udder.

Table 6: Data attribute

<table>
<tr><th>Hardware</th><th colspan="2">Parameter</th><th>Data Source</th></tr>
<tr><td rowspan="8">Flex Sensor</td><td rowspan="2">Flex Sensor 1</td><td>Udder_teat1_maxvalue</td><td rowspan="9">Collected from the sensors in the sack (Sensor Data)</td></tr>
<tr><td>Udder_teat1_minvalue</td></tr>
<tr><td rowspan="2">Flex Sensor 2</td><td>Udder_teat2_maxvalue</td></tr>
<tr><td>Udder_teat2_minvalue</td></tr>
<tr><td rowspan="2">Flex Sensor 3</td><td>Udder_teat3_maxvalue</td></tr>
<tr><td>Udder_teat3_minvalue</td></tr>
<tr><td rowspan="2">Flex Sensor 4</td><td>Udder_teat4_maxvalue</td></tr>
<tr><td>Udder_teat4_minvalue</td></tr>
<tr><td>Temperature</td><td colspan="2">Udder Temperature</td></tr>
<tr><td>Camera</td><td colspan="2">Capture the milk image – to classify as normal milk and abnormal milk</td><td>Milk Images (Milk Data). This will be combined with Sensor data to give the final data set.</td></tr>
<tr><td>Switch</td><td colspan="2">Detect the amount of udder hardness</td><td>The final Data set and the Switch data are combined and given for final processing.</td></tr>
</table>

Ithe beginning, the following parameters are considered for the dataset creation

- *Cow_id*: A unique id is given to a cow.
- *Day*: The hardware is tested on the cows at the time of lactation. The hardware was checked twice per day, morning and evening. So totally, three days *2 appropriate values have been recorded.
- *Breed of a cow*: For data collection, the local cow fields are identified. The most available breed for the experiment are Jersey and Holstein
- *House Number and address* of few farmers are noted and feedback was incorporated.
- *Months*: This parameter counts the months of a cow after giving birth to the calf.

- *Previous_Mastitis_Status*: This attribute tells about the previous occurrence of mastitis in cows
- The udder swelling is monitored using the four flex sensors, which is deployed inside the hardware sack. The following are the parameter considered from the udder
    - *IUFL*: Variations in the udder *front left* quarter at the time of *inhaling* process
    - *EUFL*: Variations in the udder *front left* quarter at the time of *exhaling* process
    - *IUFR*: Variations in the udder *front right* quarter at the time of *inhaling* process
    - *EUFR*: Variations in the udder *front right* quarter at the time of *exhaling* process
    - *IURL*: Variations in the udder *rear left* quarter at the time of *inhaling* process
    - *EURL*: Variations in the udder *rear left* quarter at the time of *exhaling* process
    - *IURR*: Variations in the udder *rear right* quarter at the time of *inhaling* process
    - *EURR*: Variations in the udder *rear right* quarter at the time of *exhaling* process
- *Temperature*: Temperature is noted at the time of lactation. Temperature varies based on environmental factors, but a high temperature (temperature greater than 46^0 C) will be taken as illness notification.
- *Hardness*: This parameter gives information about the hardness of an udder. The study says that the udder of a cow becomes more rigid at the clinical mastitis but not always the same case. The switch in the sack provides the udder hardness information and this information manually given by the cow owner. 0 indicates no hardness and 1 shows the hardness of an udder.
- *Pain*: The extreme swelling of an udder gives the pain due to which temperature increases as a sign of fever. These data are taken to detect clinical mastitis in cows.
- *Milk_Visibility*: Milk visibility also plays an essential role in detecting clinical mastitis. There will be a change in the milk pattern if clinical mastitis occurs and these patterns are captured via the camera. 0 indicates the normal and 1 indicates the abnormal condition of the milk.

Figure 18 shows the pictorial representation of data attribute points. The analysis of these data attributes tells that no parameters are directly proportional to the clinical mastitis. A

suitable algorithm is applied to get the accurate result of mastitis in cows. There are only two classes normal (0: cow without mastitis) and abnormal (1: a cow with mastitis). As per the observation, all udder quarter values from the flex sensor vary independently based on the individual cow.

Figure 19 and figure 20 represent the change in temperature value (from temperature sensor) based on the udder quarter values taken from the flex sensors. The conclusion is every value is independent but not always.

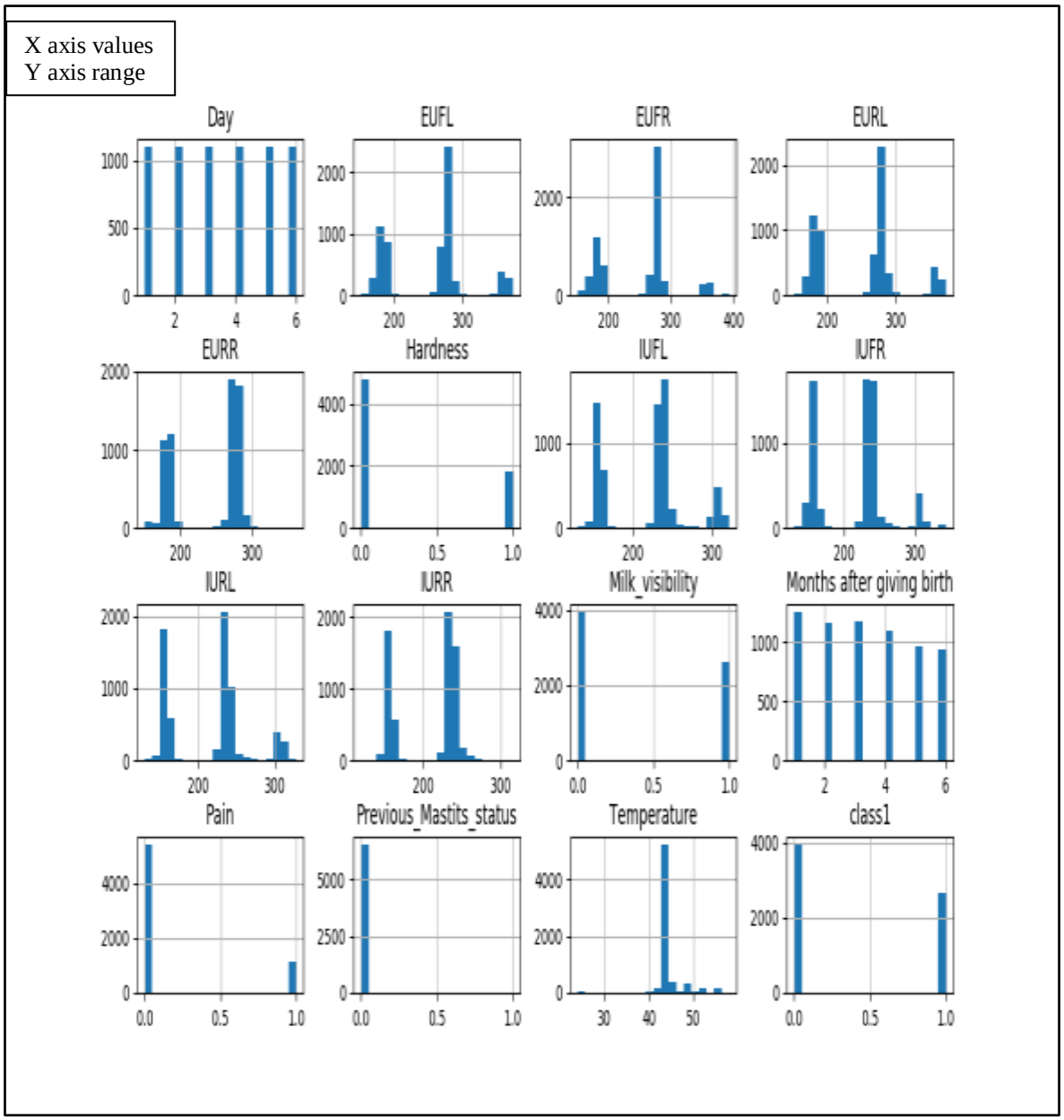

Figure 18: Pictorial representation of data attributes

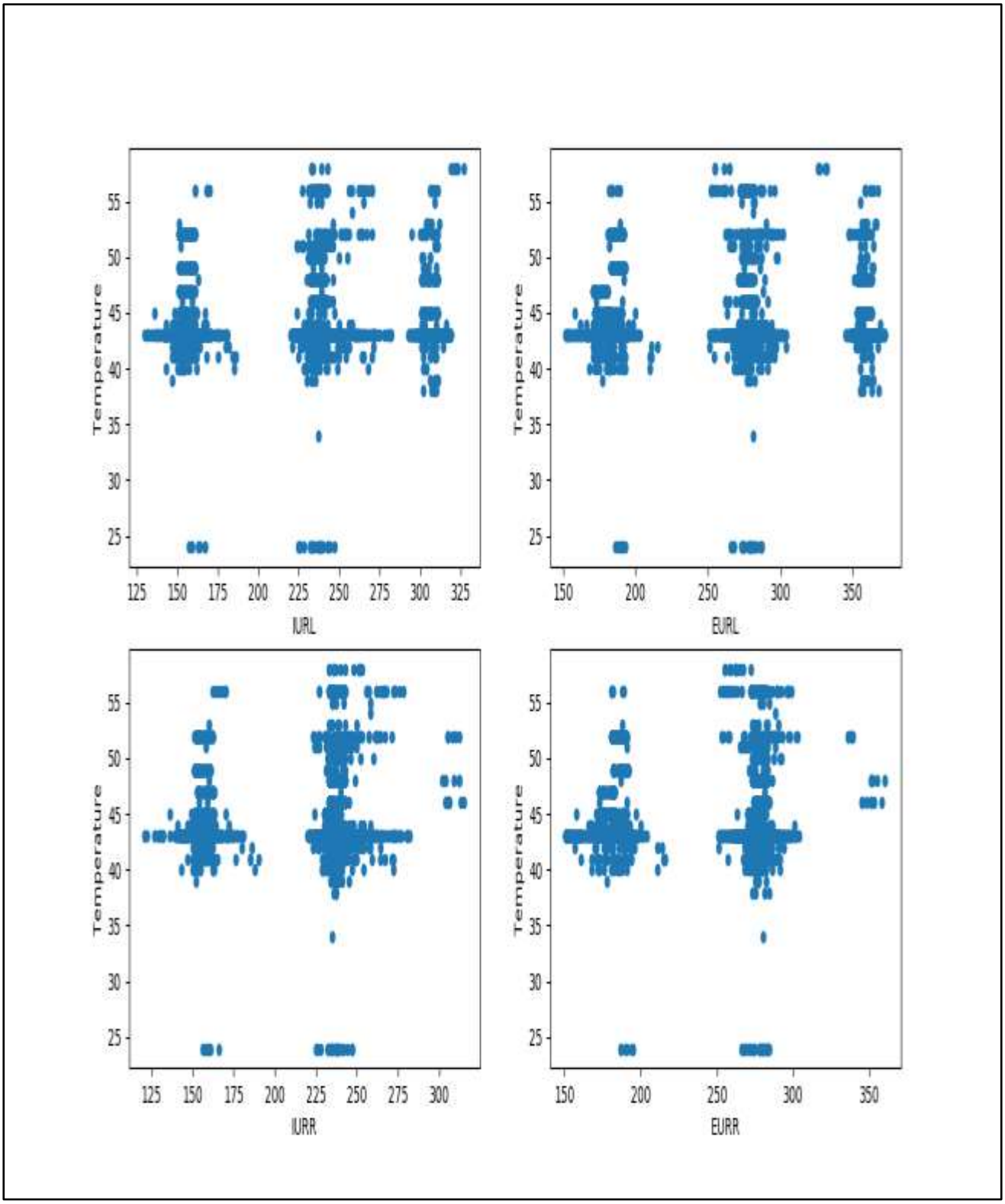

Figure 19: temperature value based on udder quarters (IURL, EURL, IURR, EURR)

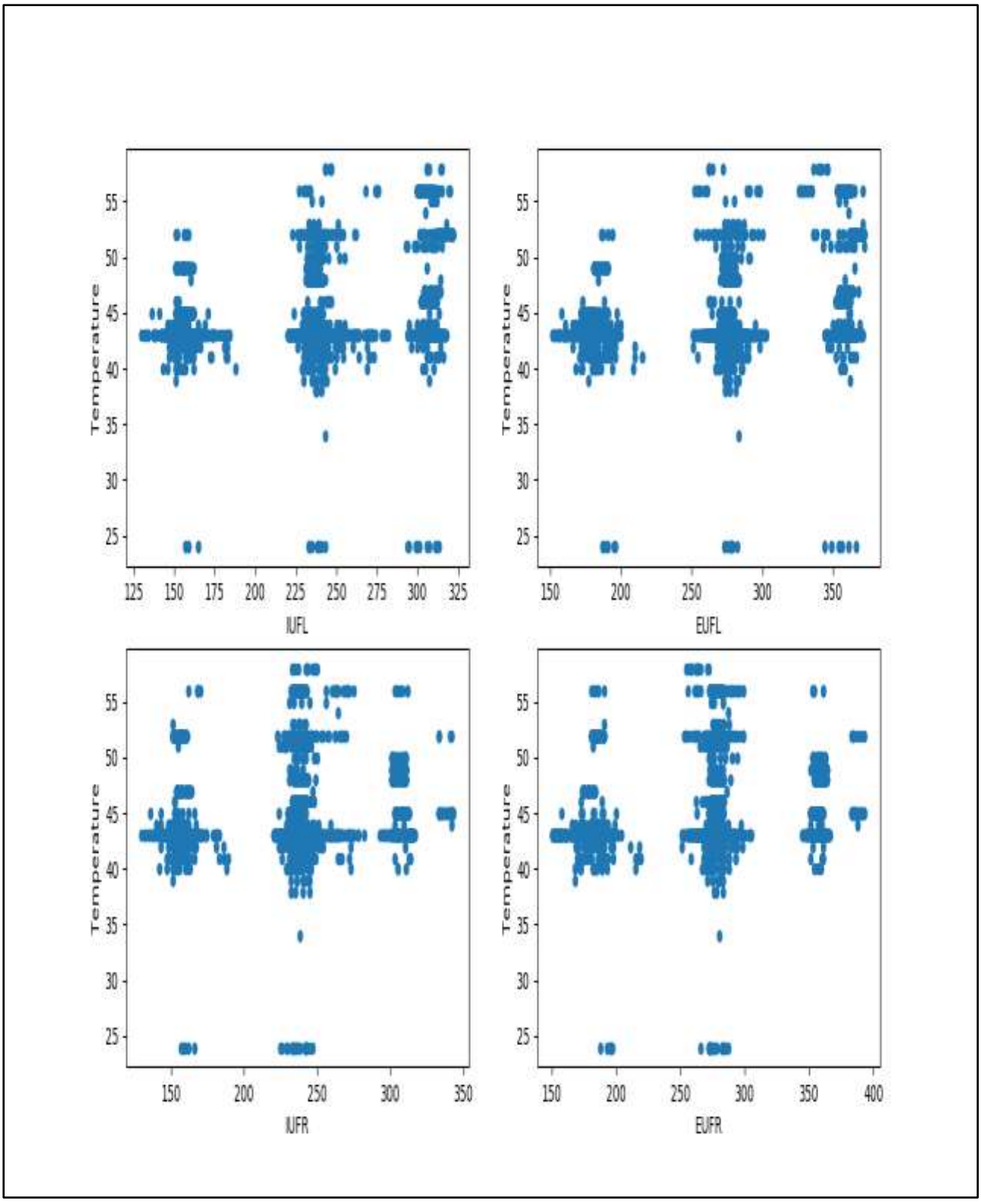

Figure 20: Temperature value based on udder quarters (IUFL, EUFL, IUFR, EUFR)

Figure 21 and Figure 22 represent the change in the value of an udder's hardness (manual input from the switch) based on the udder quarter values taken from the flex sensors. The conclusion is here, too, every value is independent but not always.

An udder's temperature and hardness are required to detect clinical mastitis, but these two parameters are not sufficient for the detection. There are various cases to increase the cow's temperature, which is not always a mastitis sign. It is difficult to find an udder's hardness in the early stage of mastitis, so an individual cannot depend on an udder's hardness for mastitis detection.

Another parameter is pain, the value of this parameter depends on the temperature value. The harness of an udder gives cow pain due to which temperature increases and leads to the fever. Figure 23 provides the relationship between temperature and pain attributes. The conclusion here is always this would not be the case. It depends on several environmental factors. Figures 24 and 25 show the flex sensor values from the udder quarter and its variation based on the local region's cow.

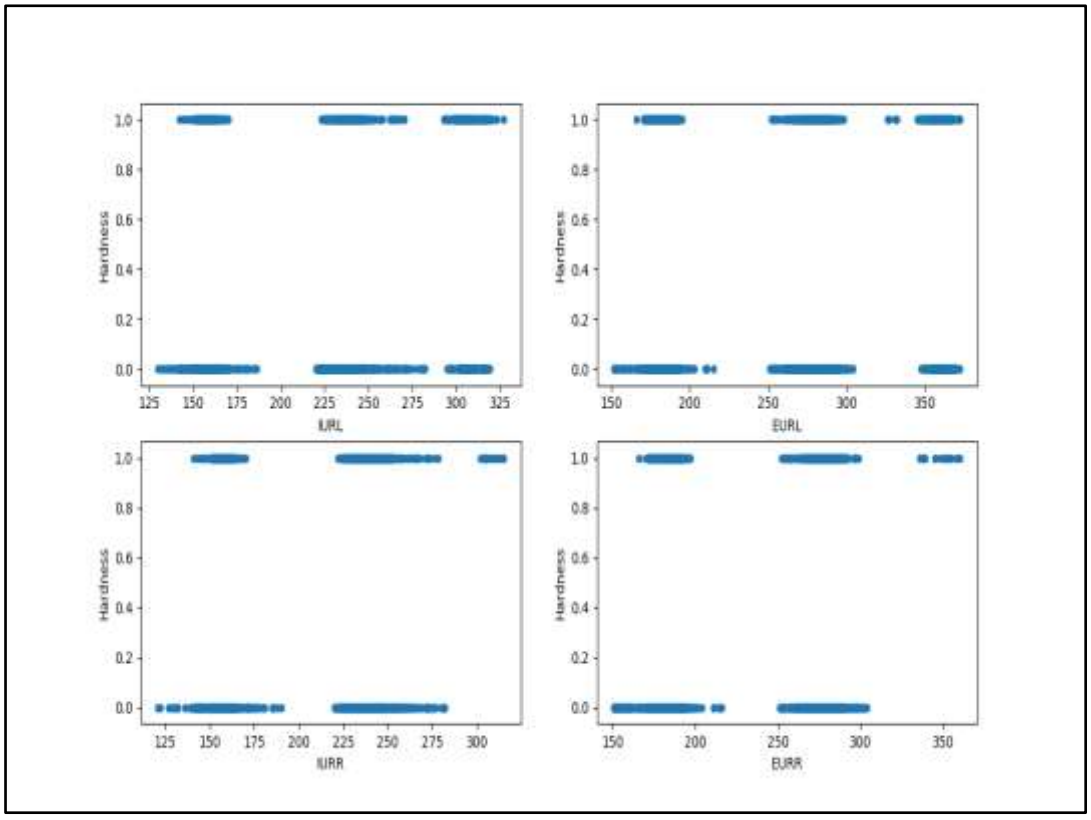

Figure 21: The hardness of an udder based on udder quarters (IURL, EURL, IURR, EURR)

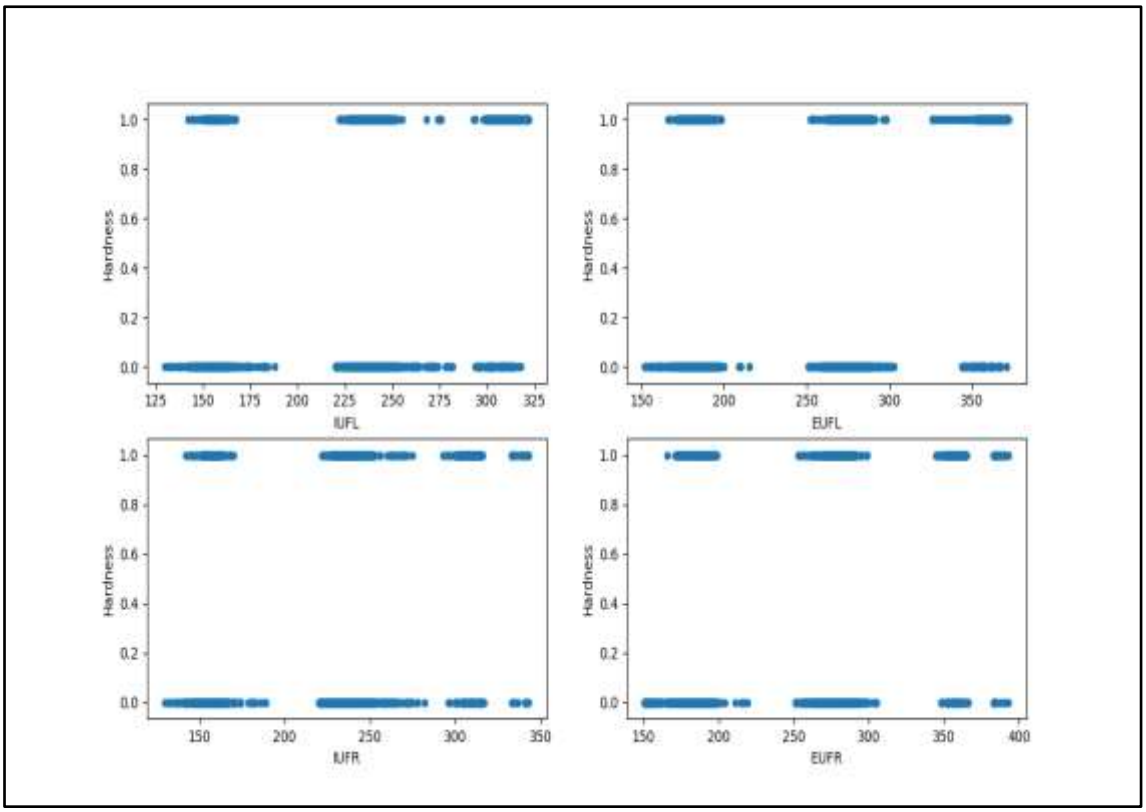

Figure 22: The hardness of an udder based on udder quarters (IUFL, EUFL, IUFR, EUFR)

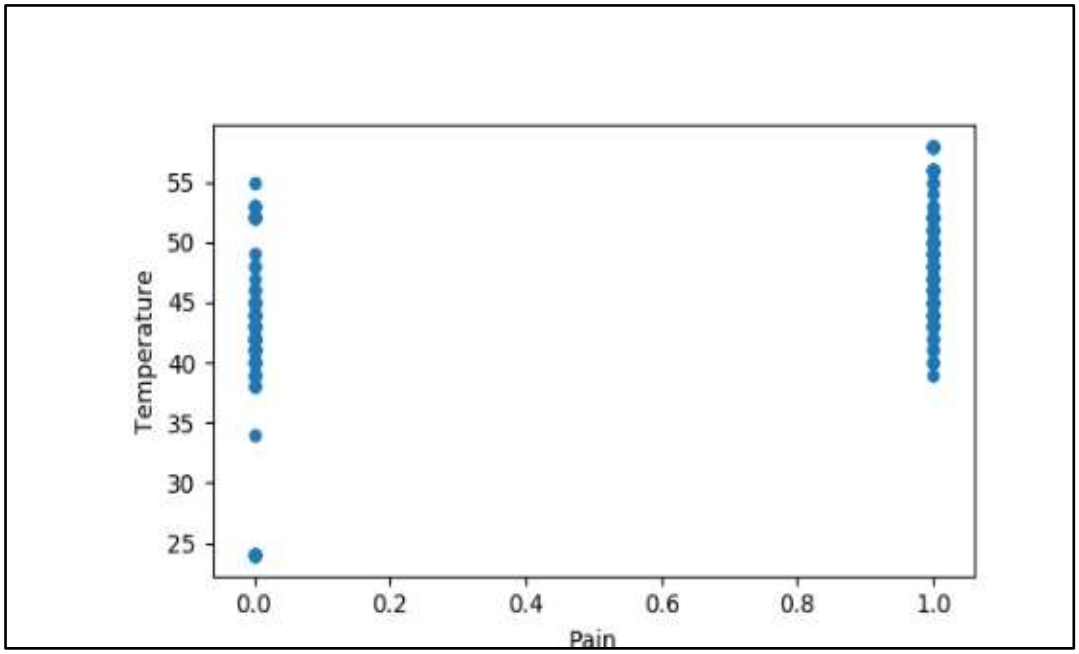

Figure 23: Relationship between temperature and pain

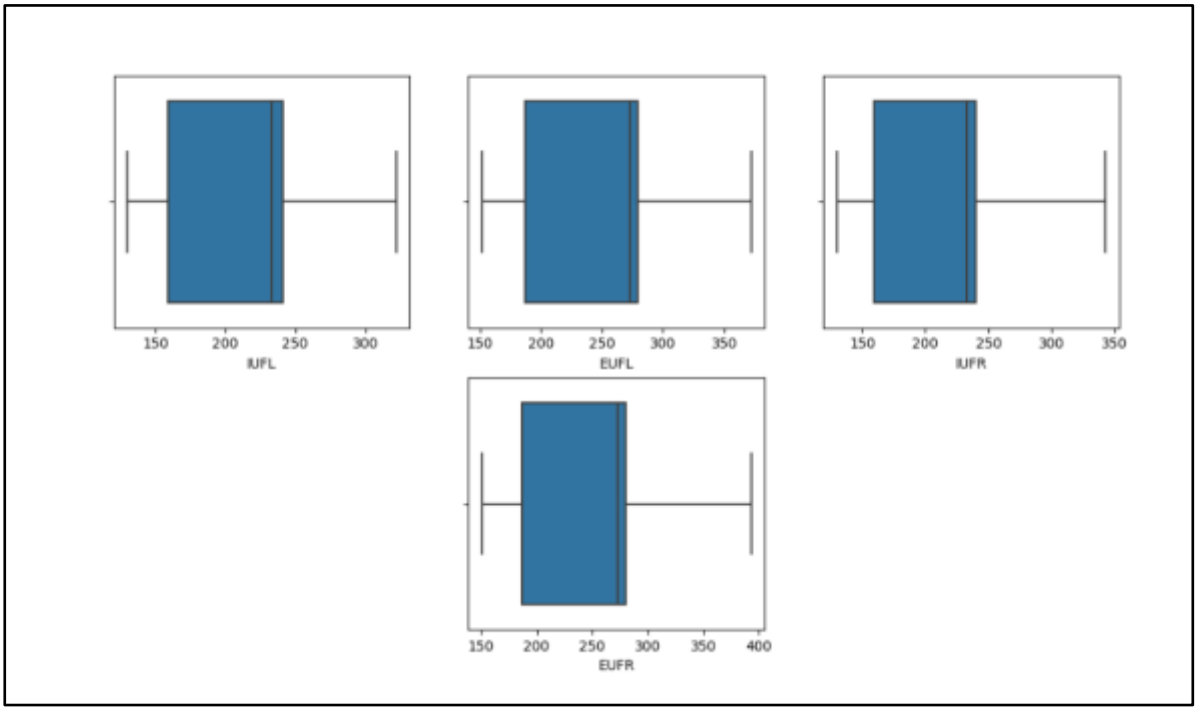

Figure 24: Representation of udder quarter values (IUFL, EUFL, IUFR, and EUFR)

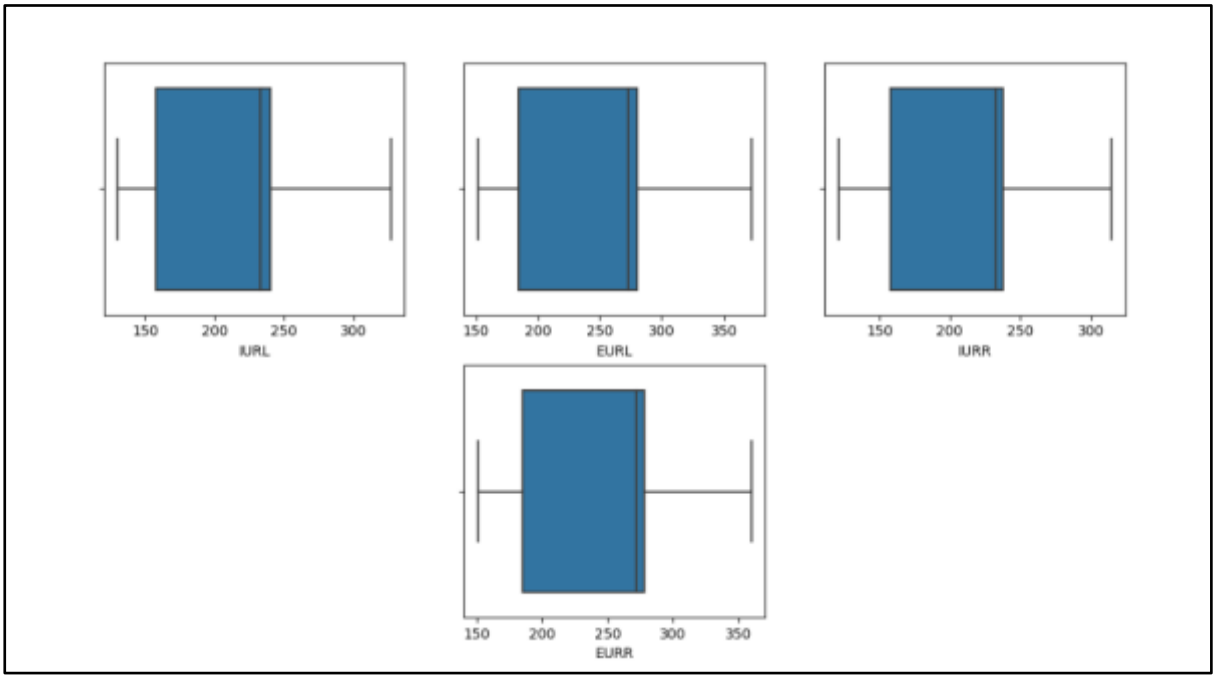

Figure 25: Representation of udder quarter values (IURL, EURL, IURR, and EURR)

Milk visibility also one of the significant attributes taken from the camera individually. Figure 26 shows the sample of normal milk image and figure 27 shows the abnormal sample image. These images are modelled and the result is transferred to the dataset prepared using sensors and switch from the hardware sack.

Figure 26: Sample of normal milk images

Figure 27: Sample of abnormal milk images

Lots of challenges faced collecting the data from the field. The data is in the form of numerical and noisy data are removed in the data pre-processing. The KDD process followed

is shown in figure 28. For further analysis, the dataset split into 70% of the training dataset and 30% of the testing dataset.

The links for dataset are,

1. https://data.mendeley.com/datasets/kbvcdw5b4m/1
2. https://data.mendeley.com/datasets/kbvcdw5b4m/2

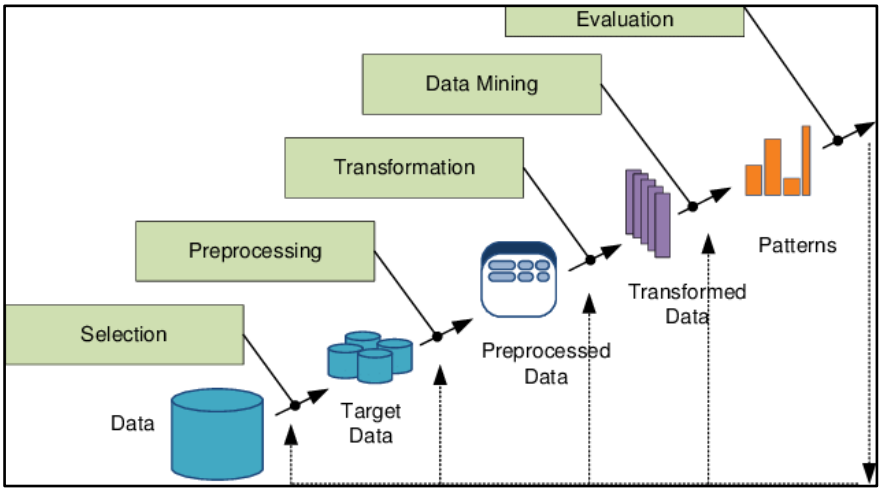

Figure 28: KDD process

10 Prediction of clinical mastitis in cows

In the beginning, the analysis is on the milk image data and output should be noted. The convolution neural network (CNN) is used to detect milk visibility of cows. The outcome will be in the binary form 0 says the milk is normal and 1 says the milk is abnormal. This information is written in the last column of the dataset for analysis. The overview of the CNN process is shown in figure 29.

The convolution neural network concept is the deep learning algorithm that uses the input image and assigns learnable biases and weights to differentiate the object from one another. CNN utilizes the hierarchical model that builds the network and finally, all neurons are combined to give single output. The CNN is a classifier used to classify the images. The CNN creates the model for further analysis and classification of the images. In the proposed system the input images are of two types abnormal milk image set and normal milk image set. The model is tested by giving various milk images for the detection of clinical mastitis.

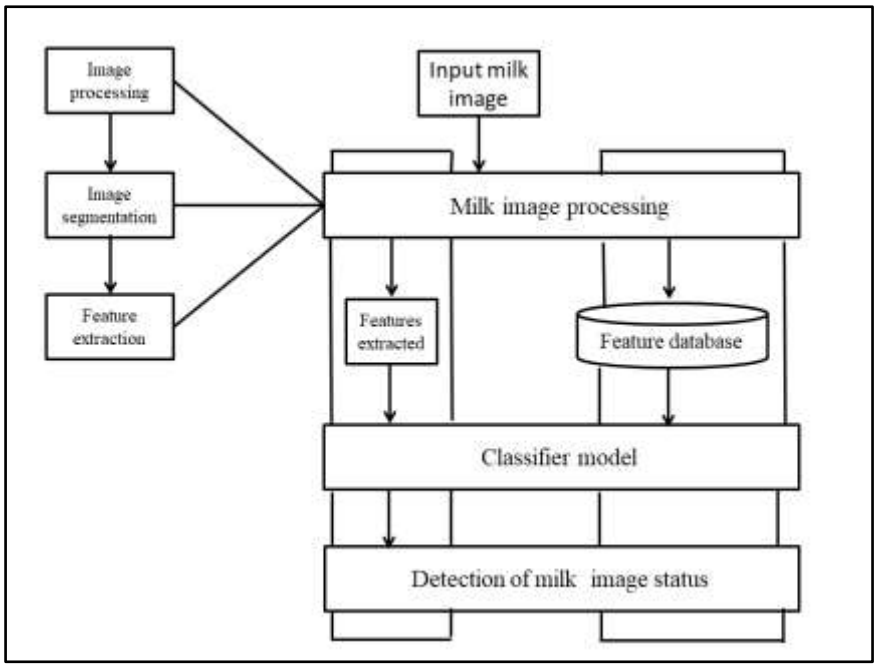

Figure 29: System architecture of CNN model

The steps of convolution neural network as follows,

Step 1: Input a milk image obtained through the camera.

Step 2: The image is resized into 60 ×60 ×3. As the proposed system is working with color images, the three channels are Red, Green and Blue.

Step 3: Splitting train and test dataset as 80% and 20%, respectively

Step 4: Convert the label into one-hot encoding. In this step, all integer data converted into binary vectors. The result provides the matrix and columns in the matrix equal the number of classes in the dataset. Figure 30 shows an example of conversion before applying the function. The respective transformation to the binary form is shown in figure 31.

Step 5: Start the convolution operations for feature maps. Here, proposed system utilizes layer by layer operation. The model building follows the sequential model, as it allows introducing layers one after the in the stack's manner. There are eight layers to process the image and the output of a layer is input to another.

```
#Labels before applying the function
#Training set labels
array([[6],
       [9],
       [9],
       ...,
       [9],
       [1],
       [1]], dtype=uint8)

#Training set labels shape
(50000, 1)

#Testing set labels
array([[3],
       [8],
       [8],
       ...,
       [5],
       [1],
       [7]], dtype=uint8)

#Testing set labels shape
(10000, 1)
```

Figure 30: Before applying the categorical function

```
#Labels after applying the function
#Training set labels
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 1]
 [0 0 0 ... 0 0 1]
 ...
 [0 0 0 ... 0 0 1]
 [0 1 0 ... 0 0 0]
 [0 1 0 ... 0 0 0]]

#Training set labels shape
(50000, 10)

#Testing set labels
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 1. 0.]
 [0. 0. 0. ... 0. 1. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 1. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 1. 0. 0.]]

#Testing set labels shape
(10000, 10)
```

Figure 31: After applying the categorical function

Layer 1: **Conv2D (input layer)**

This is the first layer in CNN that makes the input image ready for processing. It processes the two dimensional images. It has the following parameters

Filters: This specifies the height and width of the image for further processing. The filter is the small unit of the original image and continues across the image to perform the processing. Figure 32 shows the concept of filters. This filter sharpens the edges, blurs the area, and reduces the noise to prepare the processing image. A convolution filter will be applied in the first layer to detect a pattern in the image. The equation (iii) explains the output after the convolution result.

$$(M \times M) * (F \times F) = (M-F+1) \times (M-F+1) \text{ ---------- } (iii)$$

Where,

$M \times M$ *is an input image*

$F \times F$ *is a filter size*

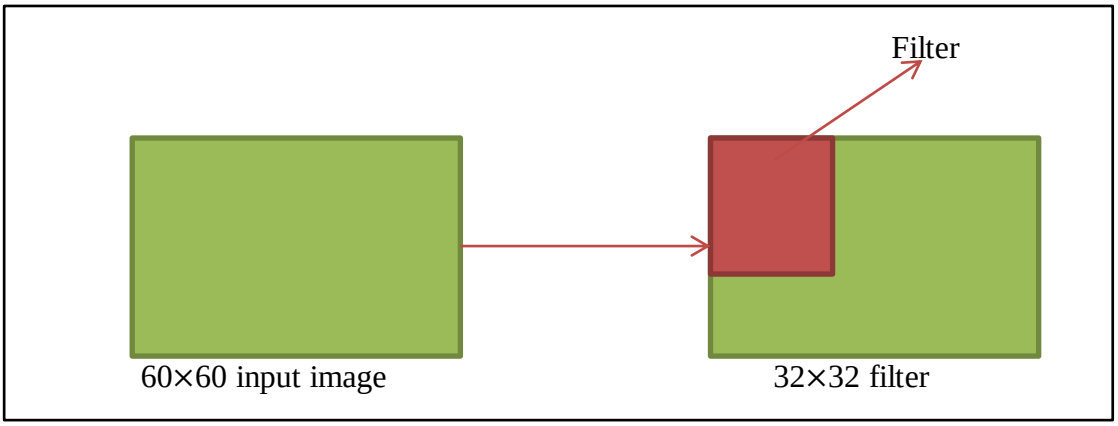

Figure 32:Filters

- *Kernel size:* This is also a kind of filter that performs the dot product between the input data sub-area and the 5×5×3 matrix to produce matrix output. The kernel of size 5×5 ×3 moves across the images to perform dot product. Figure 33 shows the dot product of the kernel and sub-area of the images.

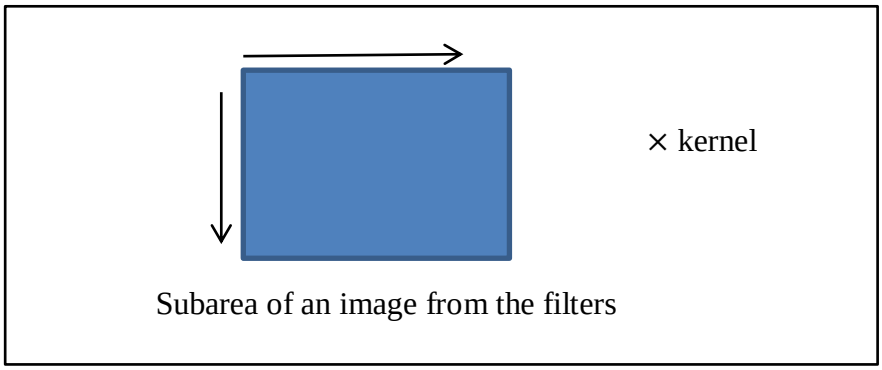

Figure 33: Kernel

- *Stride:* The stride is denoted as S. The value of S indicates every move of a window after every operation. Figure 34 shows the way of striding. By default, the string value is 1.

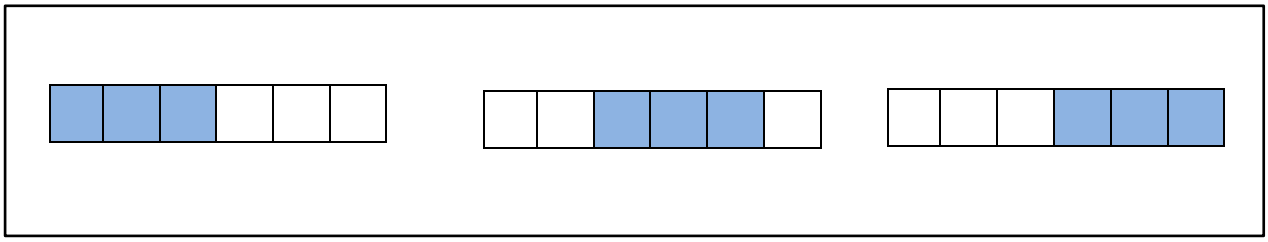

Figure 34: Striding

- *Padding:* The padding value P=0 which, adds P zeroes in the boundaries of the input image. The system uses the valid mode of padding. The equation (iv) explains the padding of an image with 0's.

$$(X+2P-F+1)x(X+2P-F+1) \text{---------- (iv)}$$

Where,

X is the size of an input

F is the filter size

P is the padding 0's

- *Activation function:* The Rectified Linear Unit (ReLU) is an activation function for nonlinear elements in the proposed work. The advantage of ReLU is, It does not activate all neurons once. Mathematically it is described as in the equation (v). The neurons are activated only if their output is greater than or equal to 0.

$$g(z)=\max(0,z) \text{ ---------- (v)}$$

Where z is input, if $z<0$, it returns 0 otherwise, the function return z.

- *Input shape:* Only in the first layer, the proposed system must shape the input for further processing. The proposed system shapes the training dataset concerning the row size. If the shape method's height and width are the same, then the image's size is taken.

Layer 2: **Conv2D (hidden layer)**

This layer takes the input from the earlier layer and performs the processing the parameter values are,

Filter = 32×32 pixel marix

Kernel = 5×5 pixel matrix

Activation function: ReLU

Layer 3: **Maxpool2D (hidden layer)**

This layer reduces the input image volume for further processing after convolution. The pooling layers present between the two convolution layers. The input image is reduced to a 2×2 image using the max pool technique.

Equation (vi) results in the width of a new image

$$W2 = (W1\text{-}F)/(S+1) \text{ ---------- (vi)}$$

Where W1 is the width of the input image,

F is the filter, S is the stride with the value 1,

W2 is the width of the new image after pooling.

Equation (vii) results in the height of a new image

$$H2 = (H1\text{-}F)/(S+1) \text{----------(vii)}$$

Where W1 is the width of the input image,

F is the filter, S is the stride with the value 1,

W2 is the width of the new image after pooling.

Equation (viii) results in the width of a new image

$$D2 = D1 \text{ ----------(viii)}$$

Where,

D2 is the depth of the new image after pooling

D1 is the depth of the input image

Layer 4: **Conv2D (hidden layer)**

This layer takes the input from the preceding layer and performs the processing the parameter values are,

Filter = 64×64 pixel matrix

Kernel = 3×3 pixel matrix

Activation function: ReLU

Layer 5: **Conv2D (hidden layer)**

This layer takes the input from the preceding layer and performs the processing the parameter values are,

Filter = 64×64 pixel matrix

Kernel = 3×3 pixel matrix

Activation function: ReLU

Layer 6: **MaxPool2D (hidden layer)**

Takes the input from the previous layer and performs the dimension reduction using 2×2 matrix.

Layer 7: **flatten (hidden layer)**

This layer converts the images into one dimensional and forwards the data to a fully connected layer. This layer creates a single long vector from the previous convolutional layer output that is MaxPool2D.

Layer 8: **Dense (fully connected layer)**

After processing an image using various convolution layers, the previous layer's output is given as input to the dense layer. The fully connected layer accepts the one dimensional matrix as an input.

Neurons: 256

Activation function: ReLU

This is a final layer that provides the output. As there are two classes for milk image normal milk and abnormal milk number of neurons set to be 2. The activation function is softmax. The softmax function works well on vector values. This function converts the input value (zero, positive, negative, or greater than one) to between 0 and 1 based on the probability.

The equation (ix) shows the mathematics of softmax

$$\sigma(\overrightarrow{Z}) = \frac{e^{Z_i}}{\sum_{j=1}^{k} e^{Z_j}} \text{ ---------- (ix)}$$

Where,

$\vec{Z}$: Input vector varies from 0 to k

Z_i: Elements of the input vectors

e^{Z_i}: Function applied on each element of the input vectors

$\sum_{j=1}^{k} e^{Z_j}$: Normalizes the value between 0 to 1, k is the number of classes.

Step 6: To avoid the over fitting of data as a part of the regularization dropout technique is applied in necessary places after adding layers. This technique ignores the few neurons while processing.

Step 7: Compile the model to specify the model architecture. It takes three parameters

1. Loss: For classification problems as per the study, the best suitable function is *categorical_crossentropy*. A lower value of a loss variable gives a better model performance. The *crossentropy* is calculated using the formula (x).

$$\text{Categorial}_{\text{crossentropy}} = -\log q(x) \text{----------(x)}$$

Where,
x is a class

2. Optimizer: As per the study, globally accepted useful optimizer is *Adam*. The optimizer controls the learning rate of the training set.
   The pseudocode for Adam is shown in algorithm 1
3. Metrics: To validate the model, the *Accuracy* metrics is used in the proposed model

Step 8: To map all parameters to the correct values of output and input *fit* method is used. In this fit method number of epochs must be mentioned to train the model. The batch is 32 and the number of epochs is 15.

Step 9: Use the model to predict dynamic input from the other end.

Step 10: Output gives either of two values, normal or abnormal, for the input milk image.

Step 11: Convert these values to binary values like 0 (normal) or 1(abnormal).

Step 12: Combine the output of Step 8 to the udder data set as last column data.

Algorithm 1. Adam optimization

Let $g(\theta)$ is an objective function, initial parameter θ_0, $\propto$ is a seep size hyper parameter, β_1 and β_2 are exponential delays, $\tau > 0$ is a tolerance parameter for numerical stability and decision rule for declaring convergence of θ_i.

1. Procedure Adam (g, θ_0, $\propto$, β_1, β_2)
2. m_0, V_0, $t \leftarrow$ [0,0,0 # Initialize moment estimates and #timestep to zero
3. # Optimization procedure starts
4. **While** θ_t has not converged **do**
5. $t \leftarrow t + 1$ # update timestep
6. $f_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ # Compute gradient of a object
7. $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot f_t$ # Update first moment estimate
8. $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot (f_t \cdot f_t)$ # Update second moment estimate
9. $\widehat{m_t} \leftarrow {}^{m_t}/_{(1-\beta_1^t)}$ # create unbiased estimate $\widehat{m_t}$
10. $\widehat{v_t} \leftarrow {}^{v_t}/_{(1-\beta_2^t)}$S # create unbiased estimate $\widehat{v_t}$
11. $\theta_t \leftarrow \theta_{t-1} - \propto \cdot \widehat{m_t}/(\sqrt{\widehat{v_t}} + \gamma$ # Update objective parameter
12. **End while**
13. **Return** θ_t # Return final parameter

In forward propagation, the input images are given to the input layer as a number. These numbers say the intensity of pixels in the images. The overall CNN works on the concept of backpropagation and the loss is calculated using the formula (xi).

Loss=predicted_output-actual_output ----------(xi)

The image dataset consists of 6600 images for analysis. At the end of the process, the system gives information about milk abnormality. This output of CNN has to be written to the udder's data to provide the outcome. Milk grade classification is shown in figure 35 and figure 36 for normal and abnormal milk, respectively.

Figure 37 show the accuracy based on the split model accuracy is 83%, validation accuracy is 82% and the model loss. The observation has validation accuracy is slightly less than the training accuracy. The accuracy and model loss are shown in figure 38 and figure 39, respectively.

Figure 35: Milk grade classification of normal milk

Figure 36: Milk grade classification of abnormal milk

```
pu_allocator_impl.cc:81] Allocation of 15676416 exceeds 10% of system memory.
2020-11-19 22:31:36.856235: W tensorflow/core/framework/cpu_allocator_impl.cc:81] Allocation of 15676416 exceeds 10% of system memory.
880/880 [==============================] - 5s 6ms/step - loss: 4.0751 - accuracy: 0.7614 - val_loss: 0.6290 - val_accuracy: 0.8227
Epoch 2/15
880/880 [==============================] - 4s 4ms/step - loss: 0.6031 - accuracy: 0.8216 - val_loss: 0.5533 - val_accuracy: 0.8273
Epoch 3/15
880/880 [==============================] - 3s 4ms/step - loss: 0.5064 - accuracy: 0.8330 - val_loss: 0.4655 - val_accuracy: 0.8273
Epoch 4/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4555 - accuracy: 0.8330 - val_loss: 0.4556 - val_accuracy: 0.8273
Epoch 5/15
880/880 [==============================] - 3s 4ms/step - loss: 0.4546 - accuracy: 0.8330 - val_loss: 0.4592 - val_accuracy: 0.8273
Epoch 6/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4519 - accuracy: 0.8330 - val_loss: 0.4609 - val_accuracy: 0.8273
Epoch 7/15
880/880 [==============================] - 3s 4ms/step - loss: 0.4590 - accuracy: 0.8330 - val_loss: 0.4581 - val_accuracy: 0.8273
Epoch 8/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4552 - accuracy: 0.8330 - val_loss: 0.4566 - val_accuracy: 0.8273
Epoch 9/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4490 - accuracy: 0.8330 - val_loss: 0.4602 - val_accuracy: 0.8273
Epoch 10/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4536 - accuracy: 0.8330 - val_loss: 0.4603 - val_accuracy: 0.8273
Epoch 11/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4540 - accuracy: 0.8330 - val_loss: 0.4603 - val_accuracy: 0.8273
Epoch 12/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4540 - accuracy: 0.8330 - val_loss: 0.4603 - val_accuracy: 0.8273
Epoch 13/15
880/880 [==============================] - 3s 4ms/step - loss: 0.4579 - accuracy: 0.8330 - val_loss: 0.4602 - val_accuracy: 0.8273
Epoch 14/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4596 - accuracy: 0.8330 - val_loss: 0.4602 - val_accuracy: 0.8273
Epoch 15/15
880/880 [==============================] - 4s 4ms/step - loss: 0.4565 - accuracy: 0.8330 - val_loss: 0.4602 - val_accuracy: 0.8273
```

Figure 37: Accuracy of CNN model

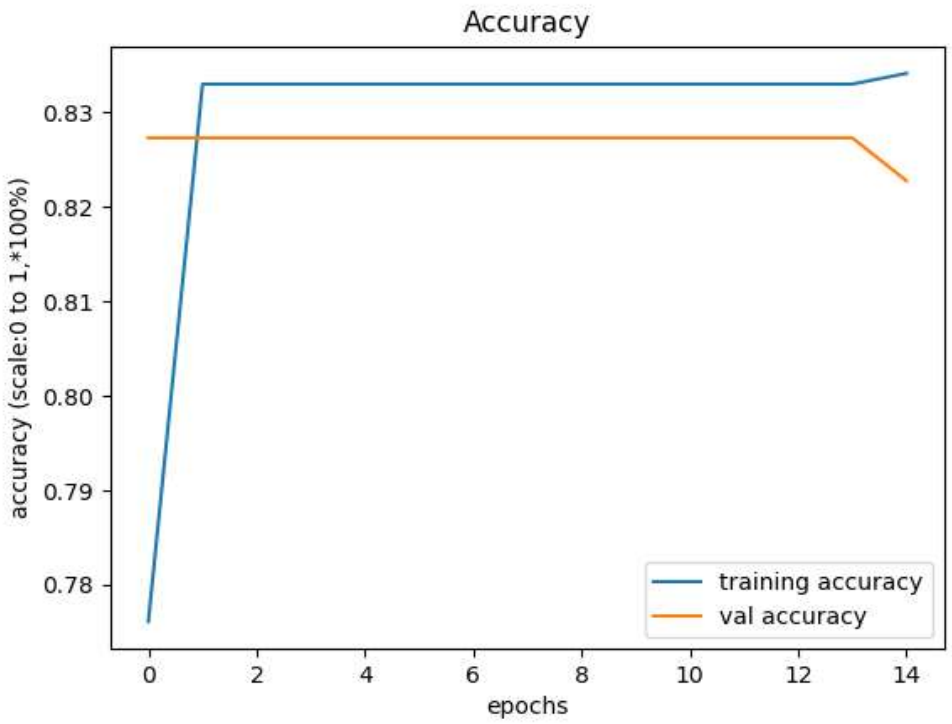

Figure 38: CNN model accuracy

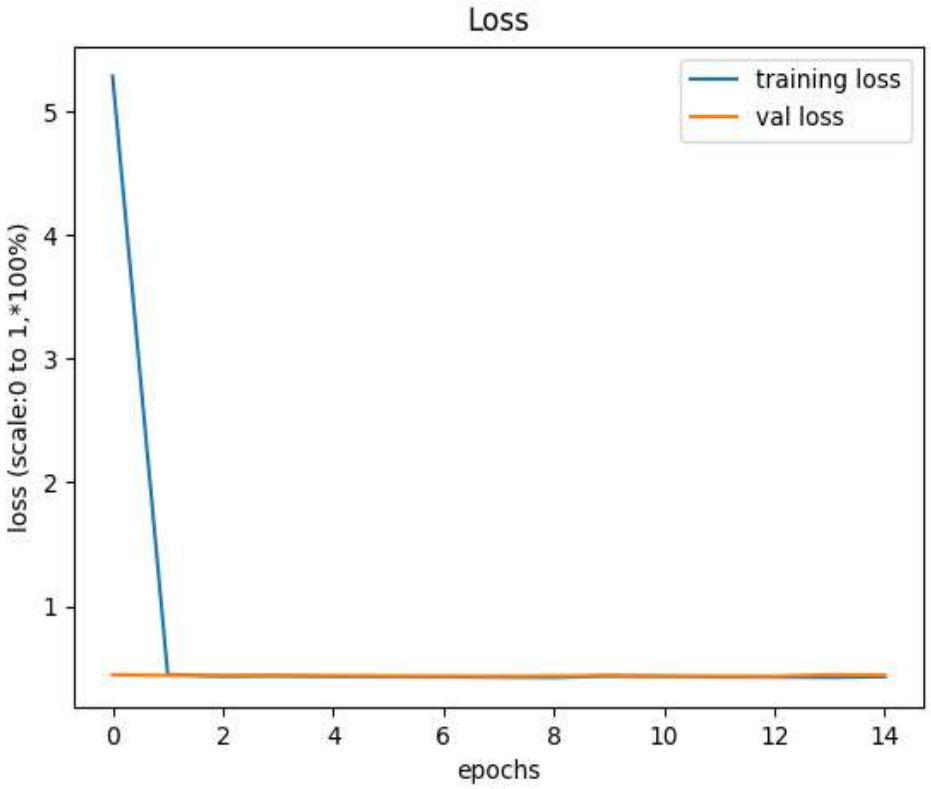

Figure 39: CNN model loss

Initially, the basic algorithm, K-nearest neighbour (KNN), is applied to the data by taking k=3, which is given the accuracy of 78.26% shown in figure 40. The confusion matrix of KNN is shown in figure 41. The distance is calculated using the Euclidean formula as shown in (xii). The pseudocode of KNN is specified in algorithm 2.

The Support Vector Machine (SVM) is applied to the primary dataset and received an accuracy of 93.57%, as shown in figure 42. The result of SVM based on confusion matrix, precession, recall, f1-score and support is shown in figure 43. The pseudocode of SVM is specified in algorithm 3.

$$\text{distance}(p, q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \quad \text{----------(xii)}$$

Where n is the number of attributes

q and p are data points.

The equation (xiii), (xiv) and (xv) gives the information of precision, recall and f1 score calculations.

$$\text{Precision} = \frac{\text{Not Mastitis}_{\text{CorrectLabeled}}}{\text{Not Mastitis}_{\text{Correctlabeled}} + \text{Mastitis}_{\text{IncorrectLabeled}}} \text{ ----------(xiii)}$$

$$\text{Recall} = \frac{\text{Not Mastitis}_{\text{Correctlabeled}}}{\text{Not Mastitis}_{\text{Correctlabeled}} + \text{Not Mastitis}_{\text{IncorrectlyLabeled}}} \text{ ----------(xiv)}$$

$$\text{f1} - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \text{ ----------(xv)}$$

Algorithm 2. K Nearest Neighbour

Let X be a training data, Y is a class label and S is a unknown sample

1. **Procedure** classify (X,Y,S)
2. **for** i=1 to m **do**
3. compute distance $D(X_i,S)$
4. **end for**
5. compute set I containing indices for the k smallest distances $d(X_i, S)$
6. **return** majority label for $\{Y_i$ where $i \in I\}$

Algorithm 3. Support Vector Machine

SVM takes the two kinds of dataset named as training and test dataset as a input. The output of SVM calculate the accuracy

1. Select the optimal value of cost and gamma for SVM
2. **While** (stopping condition is not true) **do**
3. Train the each data point using SVM
4. Classify the testing data points using SVM
5. **End While**
6. **Return** accuracy

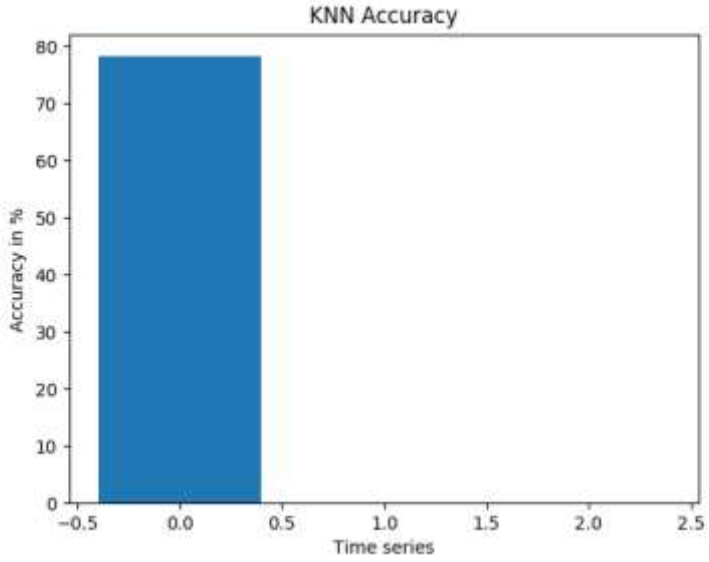

Figure 40: KNN accuracy in detecting clinical mastitis

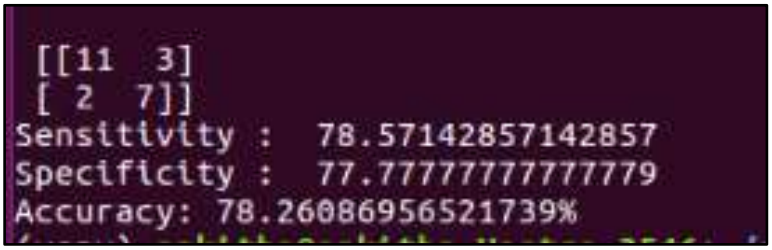

Figure 41: KNN confusion matrix

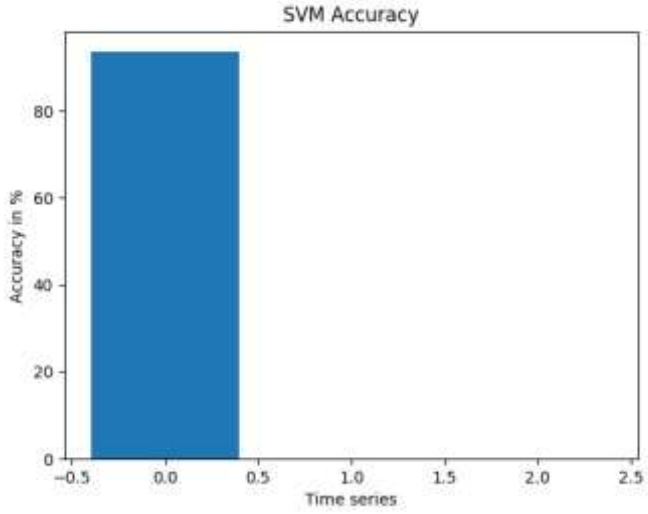

Figure 42: SVM accuracy to detect clinical mastitis

```
[[1302    4]
 [ 136  736]]
              precision    recall  f1-score   support

           0       0.91      1.00      0.95      1306
           1       0.99      0.84      0.91       872

    accuracy                           0.94      2178
   macro avg       0.95      0.92      0.93      2178
weighted avg       0.94      0.94      0.93      2178

accuracy= 93.5720844811754
Sensitivity :  99.69372128637059
Specificity :  84.40366972477065
```

Figure 43: SVM confusion matrix and result

The random forest algorithm works well to detect clinical mastitis and gives an accuracy of 93.43%. The random forest is a variant of the decision tree where it constructs many decision trees to provide an accurate result. In the proposed system, based on the dataset evaluation, the decision tree number is set to 100. Figure 44 represents the accuracy of the random forest algorithm graphically. Figure 45 shows the confusion matrix of the random forest.

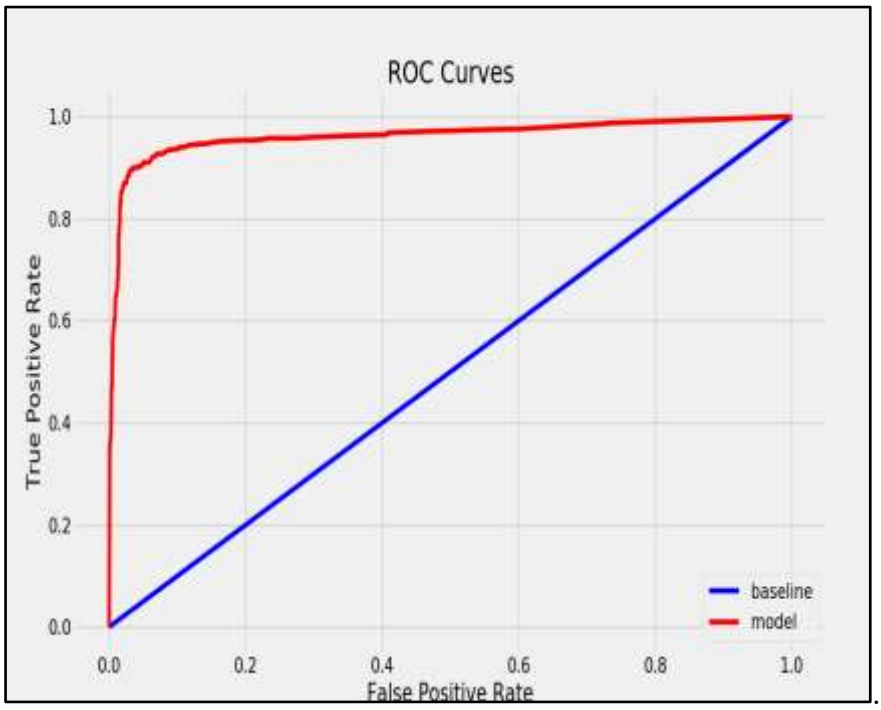

Figure 44: Random forest accuracy based on the ROC curve.

```
Confusion matrix, without normalization
[[1107   48]
 [  82  743]]
accuracy= 93.43434343434343
Sensitivity :  95.84415584415584
Specificity :  90.06060606060606
```

Figure 45: Result of the random forest algorithm

As the proposed idea deal with animal life and health, to get a better result and extract the feature automatically deep learning algorithm is applied and analyzed. Figure 46 shows deep learning methods to get better results compared to KNN, SVM, and RF.

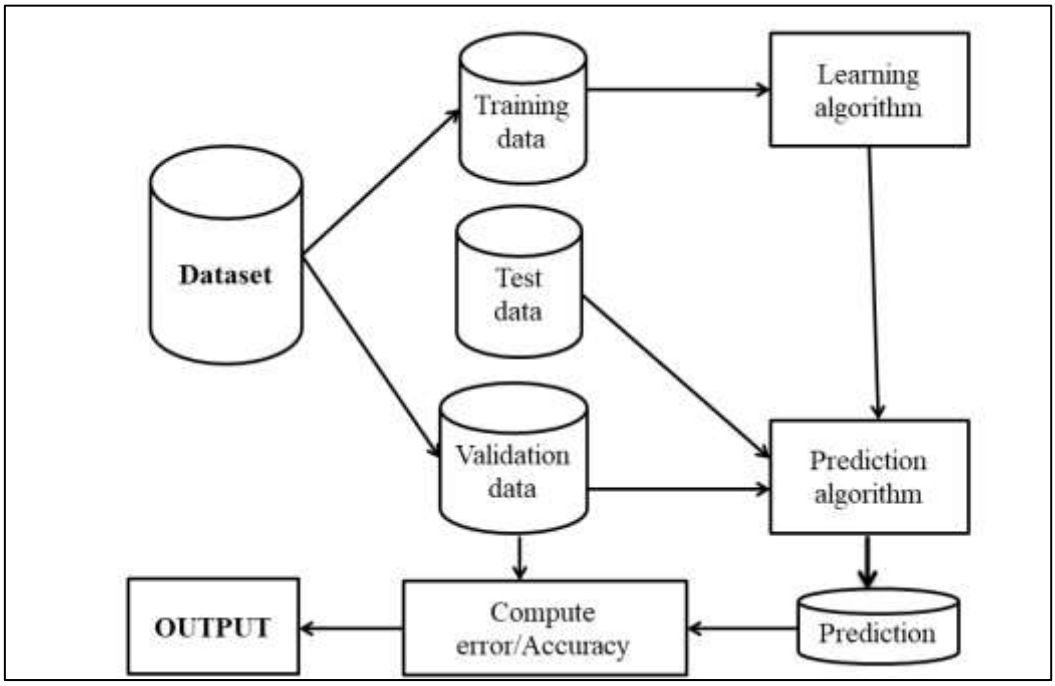

Figure 46: Deep learning process for clinical mastitis

The deep learning processes are as follows,

Step 1: Load data set.

Step 2: Normalize the data between the values 0 to 1. The new value is calculated using the formula (xvi).

$$new\_val = \frac{old\_val - min\_val}{max\_val - min\_val} \quad \text{----------(xvi)}$$

Step 3: Build a sequential model. Using the sequential model, it is possible to add a layer like a stack.

Step 4: Add layers to the sequential model build in step 3. It has three layers for processing the data.

Layer 1: **Dense layer (input layer)**

As discussed previously, the dense layer is a nonlinear. To make the process nonlinear, the data is passed through the nonlinear activation functions like ReLU and Sigmoid. Equation (xvii) shows the calculation of output y in the dense layer.

$$y = f(\text{weight} * \text{input} + \text{bias}) \text{---------- (xvii)}$$

Where f is an activation function

The parameters of dense layer are

Number of neurons = 12

Input dim = 11

Activation function = ReLU

Layer 2: **Dense layer (hidden layer)**

The attributes are,

Number of neurons = 8

Activation function = ReLU

Layer 3: **Dense layer (hidden layer)**

The attributes are,

Number of neurons = 1

Activation function = Sigmoid

The sigmoid s(x) is calculated using the formula (xviii)

$$S(x) = \frac{1}{1+e^{x}} \text{ ---------- (xviii)}$$

Step 5: Compile the model. This includes following parameters

Loss = binary_crossentropy and the binary_crossentropy is calculated using the equation (xix).

Optimizer = Adam, the pseudocode is given in the algorithm 1.

Metric =Accuracy

Step 6: Fit the model to train the dataset with the epochs of 20 and the batch size 100

Step 7: Evaluate the model for prediction and display the results.

$$\text{binary crossentropy} = -(p(x) \cdot \log q(x) + (1 - p(x)) \cdot \log(1 - q(x)))\text{-------(xix)}$$

Where x is a class

In deep learning, the features are taken automatically by the model and cross-validated. Backpropagation is a key point in deep learning. Every error is calculated and recovered in the future iteration using the concept of backpropagation. The proposed method created a three-dense layer model in deep learning with 20 epochs to detect the clinical mastitis in cows. Figure 47 and figure 48 shows the model accuracy and loss using deep learning, respectively. The confusion matrix of deep learning is elaborated in figure 49.

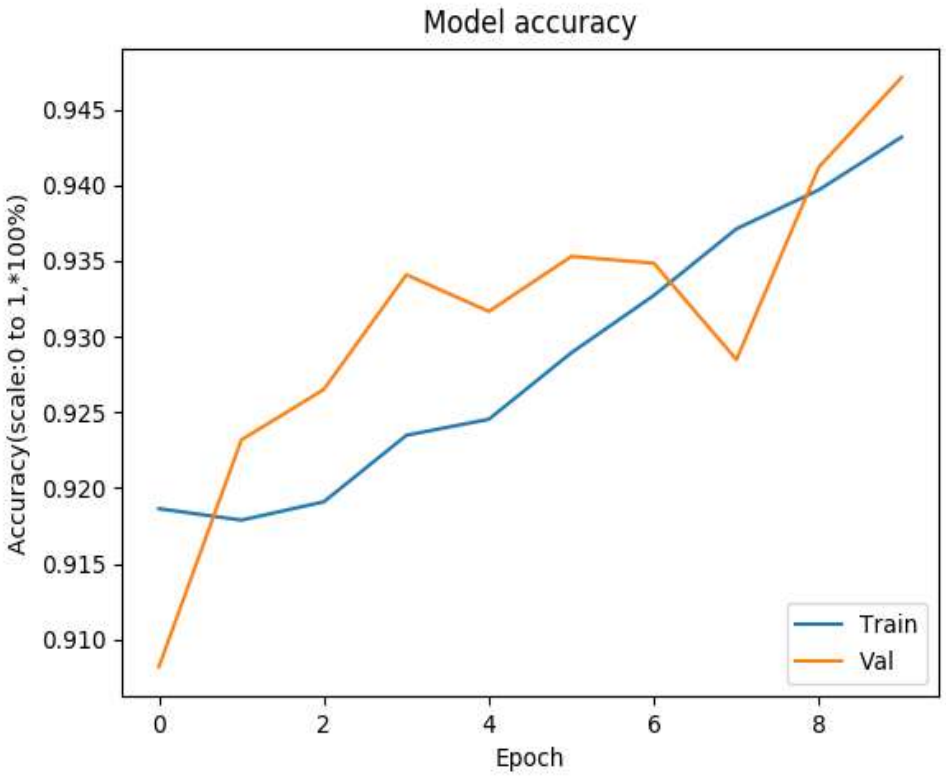

Figure 47: Deep learning model accuracy

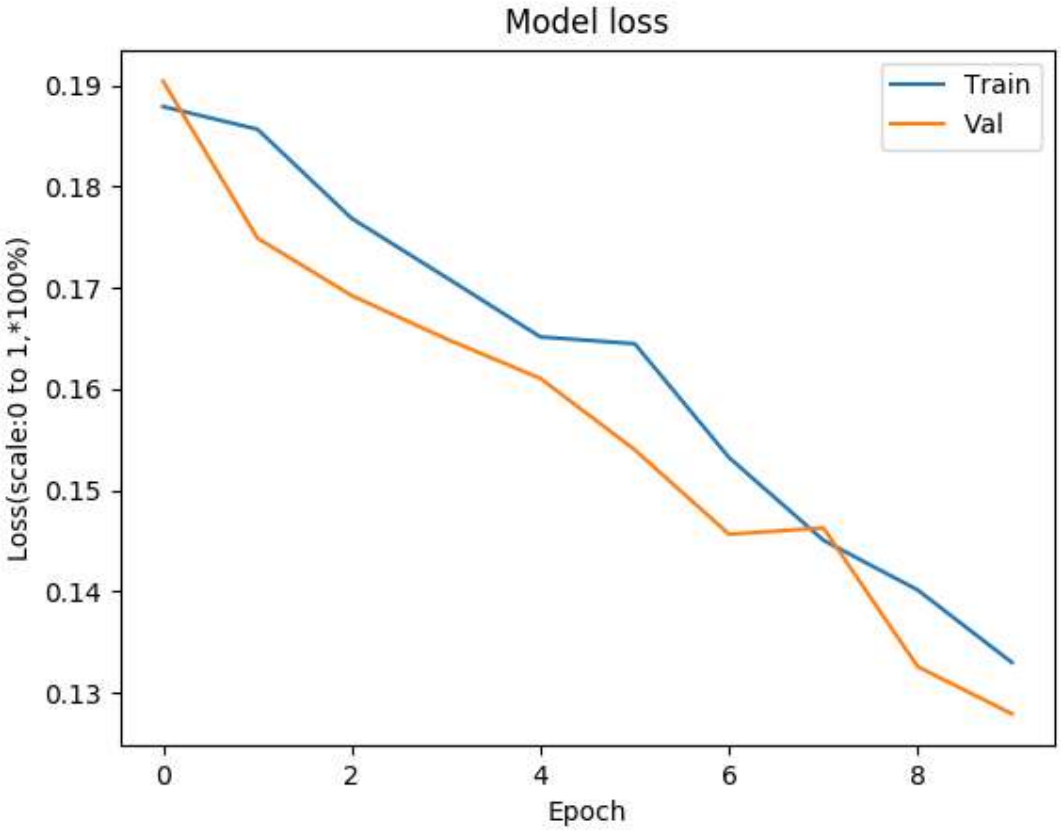

Figure 48: Deep learning model loss

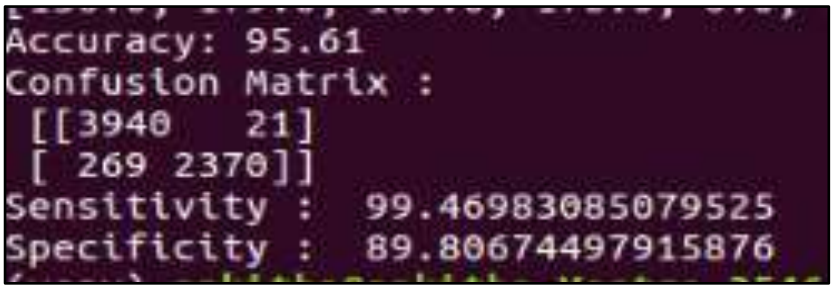

Figure 49: Deep learning confusion matrix

Table 7 compares the algorithm to the accuracy, sensitivity and specificity. The analysis shows that deep learning gives a high accurate result compared to the KNN, SVM, and RF. Using the formula (xx), accuracy is calculated.

$$Accuracy = \frac{Not\ Mastitis_{CorrectLabeled} + Mastitis_{CorrectLabeled}}{Not\ Mastitis_{Correctlabeled} + Mastitis_{CorrectLabeled} + Mastitis_{IncorrectLabeled} + Not\ Mastitis_{InCorrectLabeled}} \text{ -- (xx)}$$

With respect to the sensitivity, the RF and deep learning concept give the competitively good result. The formula (xxi) shows the result of sensitivity. Sensitivity measures how often a test correctly generates a positive result for cows that have the condition that's being tested for.

$$\text{Sensitivity} = \frac{\text{Not Mastitis}_{\text{CorrectLabeled}}}{\text{Not Mastitis}_{\text{Correctlabeled}} + \text{Mastitis}_{\text{IncorrectLabeled}}} \quad \text{----------(xxi)}$$

With respect to the specificity, the SVM and deep learning concept gives a competitively good result. The formula (xxii) gives the result of specificity.

$$\text{specificity} = \frac{\text{Not Mastitis}_{\text{CorrectLabeled}}}{\text{Not Mastitis}_{\text{Correctlabeled}} + \text{Not Mastitis}_{\text{InCorrectLabeled}}} \quad \text{---------- (xxii)}$$

Table 7: Algorithm comparison based on accuracy, sensitivity and specificity

Algorithm	Accuracy %	Sensitivity%	Specificity%
KNN	78.26	78.57	77.77
SVM	93.57	99.69	84.40
RF	93.43	85.84	90.06
Deep learning	**95.61**	**99.46**	**89.80**

11 Thesis outline

The thesis consists of 8 chapters. Chapter 1 provides an introduction to IoT and IoAHT. This includes a detailed overview of IoT in animal health things. Chapter 2 gives the background information on clinical mastitis in cows. Chapter 3 elaborates on the work carried out in animal husbandry and the problem description of the proposed work. The proposed approaches are described in detail in Chapters 4-7. Chapter 8 concludes the work.

Chapter 1: Introduction

This chapter briefs the IoT and IoAHT concepts with their challenges.

Chapter 2: Clinical mastitis in cows

This chapter provides information on clinical mastitis in cows and its challenges

Chapter 3: Identify the challenges and opportunities in detecting clinical mastitis in cows
Summarizes the work carried out in the animal husbandry using sensors and better communication protocol to detect clinical mastitis.
Chapter 4: Methodology to detect the clinical mastitis
This chapter provides a brief process and architecture to detect clinical mastitis using sensors.
Chapter 5: Hardware system to detect clinical mastitis in cows
This chapter provides a brief design of hardware to detect clinical mastitis using sensors.
Chapter 6: Data for clinical mastitis detection
Summarizes the dataset and its attribute in analysis
Chapter 7: Prediction of clinical mastitis in cows
This chapter explains algorithm utilization and its accuracy to detect clinical mastitis.
Chapter 8: Comparison of the algorithm in clinical mastitis prediction
Summarizes the result of the algorithm by comparison to find the best to detect clinical mastitis.
Chapter 9: Conclusion and future scope
This chapter concludes the thesis, summarize and discuss the limitations of the approach taken. Finally, make some suggestions for areas that feel would be benefited from future work to continue what has been accomplished in this research study.

12 List of Publication

Data set publication

1. K, Ankitha; D H, Dr. Manjaiah D H; M; (2020), "Data for: Clinical Mastitis in Cows based on Udder Parameter using Internet of Things (IoT)", Mendeley Data, V1, doi: 10.17632/kbvcdw5b4m.1. *(Dataset version 1)*
2. K, ANKITHA; Dr. Manjaiah D H, "Data for: Clinical Mastitis in Cows based on Udder Parameter using Internet of Things (IoT)", Mendeley Data, V2, doi: 10.17632/kbvcdw5b4m.2. *(Dataset version 2)*

Publications

3. Ankitha K and Dr. Manjaiah D H, "Framework to Detect Clinical Mastitis in Cows using Internet Of Animal Health Things and Deep Learning", Kala Sarovar, Vol.No.24, pp.47-57, 2021
4. Ankitha K and Dr. Manjaiah D H, "Sustainable Integration of Deep Learning and Internet of Animal Health Things to Predict Clinical Mastitis in Cows", Journal of Green Engineering, Vol. No. 10, Issue 10, pp. 9263-9280, Oct. 2020.
5. Ankitha K and Dr. Manjaiah D H, "Comparison of KNN and SVM Algorithms to Detect Clinical Mastitis in Cows Using Internet of Animal Health Things" Springer, AISC series, pp.51-60, 2020.
6. Ankitha K, Dr. Manjaiah D H, "Survey on Animal Health care system in veterinary Science using Internet of Things", International Journal of Emerging Research in Management and Technology, Vol.6, pp.357-364, DOI: 10.23956/ijermt, May 2017.
7. Ankitha K, Dr. Manjaiah D H, "Sensors for Internet of Animal Health Things", research article in CSI communications (IoT for Flora and Fauna), Vol. No. 42, Issue 3, pp. 30-31, June 2018.

13 Conclusion

IoT has profound real-time applications, with the majority being concentrated on Health Care. Much work has been focused on human health care. Animals are also an essential part of the world and ensuring their well-being is necessary. Animals, when connected to the internet, give rise to IoAHT. Clinical mastitis is an infectious disease that occurs in cows, highly contagious and proves to be life-killing if suitable measures are not taken at the early stages. The proposed work considers a combination of udder information and the milk quality data to detect clinical mastitis in cows. The udder information is primarily obtained through various sensors and switch, whereas the milk information is collected through the milk images using a camera.

Proposed system implemented CNN for better results, which brought in the accuracy of 82% with a split ratio of 80:20 of 6600 images, i.e., 80% of training images and 20% of testing images. The plan is to work with different milk images and achieve more efficient milk segmentation in the future. Working with a larger dataset will be more challenging in this aspect.

The CNN model classifies the results in the binary form – 0 for normal and 1 for abnormal. The binary information is combined with the sensor data and is further processed. The machine learning algorithms such as KNN, SVM and RF provides the mastitis detection accuracy of 78%, 93.57% and 93.43. To achieve higher accuracy, deep learning is applied to the data, enabling the model to achieve an accuracy of 95.61%. The deep learning technology provides a much better result in the detection of clinical mastitis.

14 References

[1] A Krvavica, L Likar, A Domanjkoand V Avbelj, "Compression of Wireless Electrocardiographic Monitoring and Standard ECG in dogs", IEEE International Conference Information and Communication Technology, Electronics and Microelectronics (MIPRO), pp. 396-399, July 2016.

[2] Anitha Ilapakurti and Chandrasekar Vuppalapati, "Building an IoT Framework for Connected Dairy", IEEE International Conference on Big Data Computing Service and Applications,pp. 275-285, 2015.

[3] Anushka Patii, Chetana Pawar, Neha Patii and Rohini Tambe, "Smart Health Monitoring System for Animals", IEEE International Conference on Green Computing and Internet of Things,pp. 1560-1563, 2015.

[4] Baik-Woo Lee Seong Woon Booh and Kunsoo Shin, "Embedded Discrete Passives Technology for Bandage-Type Medical Sensors of E-Healthcare System", IEEE International Conference on Electronic Components and Technology, pp.1325-1331, 2011.

[5] C. Kamphuis et. al., "Detection of clinical mastitis with sensor data from automatic milking systems is improved by using decision-tree induction", Journal of Dairy Science, Vol. 93 No. 8, pp. 3616-3627, 2010

[6] Chakchai So In et. al., "Mobile Animal Tracking Systems Using Light Sensor for Efficient Power and Cost Saving Motion Detection", IEEE International Symposium on the Communication system, Networks and Digital Signal Processing, 2012.

[7] Chao-Hsi Huang, Pin-Yin Shen and Yueh-Cheng Huang, "IoT-Based Physiological and Environmental Monitoring System in Animal Shelter", IEEE International Conference on Ubiquitous and future networks,pp. 317-322, 2015.

[8] Daniel Smith, Scott Lyle, Al Berry, Nicola Manning, Mohamed Zaki and Andy Neely " Internet of Animal Health Things (IoAHT) Opportunities and Challenges", a case study, Cambridge Service Alliance.

[9] Daphneny Stavroula Zois, "Sequential Decision Making in Healthcare IoT: Real Time Health Monitoring, Treatments and Interventions", IEEE International Conference on the Internet of Things (WF-IoT), pp. 24-29, 2016.

[10] Definition online available at https://www.leverege.com/iot-ebook/what-is-iot#:~:text=%E2%80%9CThe%20Internet%20of%20Things%20(IoT,%2Dto%2Dcomputer%20interaction.%E2%80%9D

[11] E. Wang and S. Samarasinghe, "Online Detection of Mastitis in Dairy Herds Using Artificial Neural Networks", IEEE, pp.273-278, 2015

[12] Fabian Hoflinger *et. al.,* "Motion capture sensor to monitor movement patterns in animal models of the disease", IEEE International Conference on Circuits and Systems, 2015.

[13] H. Mollenhorsta, *et. al.,* "Decision-tree induction to detect clinical mastitis with automatic milking", Elsevier, pp. 6-68, 2010

[14] H. Mollenhorst *et. al.,* "Somatic cell count assessment at the quarter or cow milking level", Journal of Dairy Science, Vol. 93, pp. 3358-3364, July 2010.

[15] Hai Wang, Abraham O. Fapojuwo and Robert J. Davies "A Wireless Sensor Network for Feedlot Animal Health Monitoring", IEEE International Sensors Journal, Volume: 16, pp. 1 -14, June 2016.

[16] Henk Hogeveen *et. al. ,* "Sensors and Clinical Mastitis the Quest for the Perfect Alert", Journal of Dairy Science, pp.7991-8009,2010

[17] Importance of cow, online available at http://www.stephen-knapp.com/importance of the cow in culture.htm

[18] Information online available at https://www.wipro.com/business-process/what-can-iot-do-for-healthcare-/

[19] J. Lu et.al., "Miniaturization and Packaging of Implantable wireless sensor nodes for Animals Monitoring", IEEE International Conference on sensors , 2016.

[20] Jun Xu G, urkan Solmaz, Rouhollah Rahmatizadeh, Damla Turgut and Ladislau Boloni, "Animal Monitoring with Unmanned Aerial Vehicle-Aided Wireless Sensor Networks", IEEE International Conference on local Computer Networks, pp.125-132, 2015.

[21] Kriti Bhargava, Stepan Ivanov, Chamil Kulatunga and William Donnelly, "Fog-enabled WSN System for Animal Behaviour Analysis in Precision Dairy", IEEE International Conference on Computing, Networking and Communications (ICNC), 2017.

[22] Lucia Pepa, Marianna Capecciy, Federica Verdini, Maria Gabriella Ceravoloy and Luca Spalazzi, "An Architecture to Manage Motor Disorders in Parkinson's Dis- ease", IEEE International conference on Internet of Things (WF-IoT), 2015.

[23] Martin Hierold et. al., "Low-weight Wireless Sensor Node for Animal Encounter Detection and Dual-band Localization", IEEE Topical Conference on Wireless Sensors and Sensor Networks, pp. 21-23, 2016.

[24] Michael Schadhauser, Joerg Robert and Albert Heuberger, "Concept for an Adaptive Low Power Wide Area (LPWA) Bat Communication Network", IEEE, European Conference on Smart Objects, Systems and Technologies, pp.75-83, June 2016.

[25] Mohamad Y. Mustafa, Svein M. Eilertsen and Amund Kronen, "Matching Mother and Calf Reindeer Using Wireless Sensor Networks", IEEE International Conference on Computer Science and Information Technology, pp. 99-105, 2013.

[26] Muhammad Hunain Memon et. al., "Internet of Things (IoT) Enabled Animal Farms", IEEE International Conference on Computing for Sustainable Global Development, pp.2067-2072, 2016.

[27] Namkyung Lee HyunKeuk Lee and HyunWoo Lee, "Things-Aware Smart Pet- Caring System with the Internet of Things on Web of Object Architecture", IEEE International Conference on Information and Communication Technology Convergence (ICTC), pp.1247-1252, 2016.

[28] On-line available at https://www.pubs.ext.vt.edu/404/404-233/404-233.html#:~:text=Mastitis%20occurs%20when%20the%20udder,ducts%20throughout%20the%20mammary%20gland

[29] On-line available at https://www.statista.com/chart/20110/biggest-producers-of-milk-in-the-world/#:~:text=India%20has%20the%20biggest%20milk,produce%20in%20a%20year%20combined.

[30] Rachit Singh and G. M. Asutkar, "Survey on various Wireless Sensor Network Techniques for Monitoring Activities of Wild Animals", IEEE International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), 2015.
[31] RW Claycomb *et. al.,* "An automated in-line clinical mastitis detection system using measurement of conductivity from foremilk of individual udder quarters", New Zealand Veterinary Journal, pp. 208-214, 2009.
[32] Sanat Sarangi *et. al.,* "Development of a Wireless Sensor Network for Animal Management: Experiences with Moosense", IEEE International Conference on Advanced Networks and Telecommuncations Systems (ANTS),pp.1-6, 2014.
[33] Sangeetha Rajesh, "Ubiquitous Energy Efficient Aquaculture Management System", IEEE International Conference on Advances in Computing, Communications and Informatics, pp.1124-1127, 2016.
[34] Shubham Saloni and Achyut Hegde, "WiFi-Aware as a Connectivity Solution for IoT", IEEE International Conference on Internet of Things and Applications, pp.137-142, 2016 .
[35] Technology in veterinary science, online available at http://carrington.edu/blog/veterinary/newest-advances-veterinary-technology/
[36] Udder turns to red, online available at, http://explainagainplease.blogspot.com/2012/10/cow-health-mastitis-and-teat-injuries.html
[37] Udit Satija, Barathram.Ramkumar, and M. Sabarimalai Manikandan, "Real-Time Signal Quality-Aware ECG Telemetry System for IoT-Based Health Care Monitoring", IEEE Internet of Things Journal,pp. 1-9, Feb. 2012.
[38] Udit Sajjanhar and Pabitra Mitra, "Distributive Energy Efficient Adaptive Clustering Protocol for Wireless Sensor Networks", IEEE International Conference on Mobile Data Management, pp.326-330, 2007.
[39] Wendi B. Heinzelman and Anantha P. Chandrakasan, "An Application-Specific Protocol Architecture for Wireless Microsensor Networks", IEEE transactions on wireless communications, Vol. 1, No. 4, pp. 660-670, October 2002.
[40] Wen-Tsai Sung, Jui-Ho Chen, Da-Chiun Huang and Yi-Hao Ju, "Multisensors Realtime Data Fusion Optimization for IoT Systems", IEEE International Conference on Systems, Man, and Cybernetics, pp. 2299-2304, 2014.
[41] Xing Chen and Darrin Young, "Robust Implantable Blood Pressure Sensor Packaging for Long-Term Laboratory Animals Monitoring", IEEE International Conference on sensors, 2016.
[42] Zhibin Sun *et. al.,* "Detection of mastitis and its stage of progression by automatic milking systems using artificial neural networks", Journal of Dairy Research, pp.168-175, 2010

Research Candidate — Research Supervisor

Ankitha K — Dr. Manjaiah D.H,

Department of Post-Graduate Studies and Research in
Computer Science
Mangalore University
Mangalagangothri